Improving the sustainability of coal SC in both developed and developing countries by incorporating extended exergy accounting and different carbon reduction policies

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Abstract

Improving the sustainability of coal SC in both developed and developing countries by incorporating extended exergy accounting and different carbon reduction policies

Ali Roozbeh Nia, Ph.D.

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In the age of Industry 4.0 and global warming, it is inevitable for decision-makers to change the way they view the coal supply chain (SC). In nature, energy is the currency, and nature is the source of energy for humankind. Coal is one of the most important sources of energy which provides much-needed electricity, as well as steel and cement production. This manuscript-based PhD thesis examines the coal SC network as well as the four carbon reduction strategies and plans to develop a comprehensive model for sustainable design. Thus, the Extended Exergy Accounting (EEA) method is incorporated into a coal SC under economic order quantity (EOQ) and economic production quantity (EPQs) in an uncertain environment. Using a real case study in coal SC in Iran, four carbon reduction policies such as carbon tax (Chapter 5), carbon trade (Chapter 6), carbon cap (Chapter 7), and carbon offset (Chapter 8) are examined. Additionally, all carbon policies are compared for sustainable performance of coal SCs in some developed and developing countries (the USA, China, India, Germany, Canada, Australia, etc.) with the world's most significant coal consumption. The objective function of the four optimization models under each carbon policy is to minimize the total exergy (in Joules as opposed to Dollars/Euros) of the coal SC in each country. The models have been solved using three recent metaheuristic algorithms, including Ant lion optimizer (ALO), Lion optimization algorithm (LOA), and Whale optimization algorithm (WOA), as well as three popular ones, such as Genetic algorithm (GA), Ant colony optimization (ACO), and Simulated annealing (SA), are suggested to determine a near-optimal solution to an exergy fuzzy nonlinear integer-programming (EFNIP). Moreover, the proposed metaheuristic algorithms are validated by using an exact method (by GAMS software) in small-size test problems. Finally, through a sensitivity analysis, this dissertation compares the effects of applying different percentages of exergy parameters (capital, labor, and environmental remediation) to coal SC models in each country. Using this approach, we can determine the best carbon reduction policy and exergy percentage that leads to the most sustainable performance (the lowest total exergy per Joule). The findings of this study may enhance the related research of sustainability assessment of SC as well as assist coal enterprises in making logical and measurable decisions.

"To my father, in loving memory"

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Contribution of Authors

Ali Roozbeh Nia: Conceptualization, Methodology, Software, Writing- Original draft preparation, Validation, Writing-Reviewing and Editing

Anjali Awasthi: Supervision, Writing-Reviewing and Editing.

Nadia Bhuiyan: Supervision, Writing-Reviewing and Editing.

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List of Acronyms

CH4: Methane

CO2: Carbon dioxide

EEA: Extended Exergy Accounting

EOQ: Economic order quantity

EPQ: Economic production quantity

EMQ: Economic manufacturing quantity

EFNIP: Exergy fuzzy nonlinear integer-programming

FST: Fuzzy set theory

N2O: nitrous oxide

O3: Ozone

SC: Supply chain

SVMB: Single-vendor multi-buyer

VMI: Vendor managed inventory

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CHAPTER 1. INTRODUCTION

1.1. Energy market

The energy market is a type of commodity market handling process specifically with the trade and provision of energy, which may refer to electricity, heat, and fuel products. Major commodities being natural gas and electricity while other commodities traded in the energy market are oil, coal, carbon emissions (greenhouse gases), nuclear power, solar energy, and wind energy. Energy markets are known as a fast-growing and complicated sector considering their significant role in the global economies, the necessity of this sector in power and gas supply, and financial concerns of energy (Mousavi et al. 2021).

It is true that the energy market today tends to be maturing and unbalanced, characterized by increasing demand and fluctuating supply (Roozbeh Nia et al., 2021). There are tangible signs to verify that demand and price are not predetermined and can influence a broad collection of market influences and customer behaviors. For example, due to the difficulty in storing and transporting energy, current and future prices in energy are rarely linked. This is because energy purchased at current prices is difficult to store and sell later. While some scholars have focused on the direct issues, there are also unforeseen issues such as the economic environment, business events, and global politics (Su et al., 2021). In the last two decades, the global economy and energy market has witnessed several uncertainty-inducing events. Examples of such events include: the 2007–2009 Global Financial Crisis, also known as the Great Recession; the escalating global trade disputes, especially the trade tensions between the United States and China that degenerated in 2018 and 2019; the BREXIT vote and the subsequent negotiations between the United Kingdom and the European Union; the March 2020 oil price war between Russia and Saudi Arabia; the European sovereign debt crisis; the COVID-19 pandemic that crippled economic activities globally; and the ongoing Russia-Ukraine war that has led to the imposition of sanctions on Russia by many countries, especially European countries (Ogbuabor et al. 2023). As a result, many countries have re-evaluated their energy sources. The fact is that uncertainties in demand and energy consumption significantly affect the total supply chain (SC) cost as the penalty cost of unsatisfied demand increases (Priyan et al. 2022). In response to this issue, Zadeh (1965) proposed "fuzzy set theory (FST)," which translates "ill-defined" data into mathematical terms.

The energy division is segregated into various sections, each with their own SC problems and challenges. The common five sub-sectors in the energy SC division are Oil & gas upstream, Oil & gas downstream, Chemicals & petrochemicals, Mining and Power & utilities. (Roozbeh Nia et al. 2021). Management of energy is critical for economic success and environmental security since energy is connected to many sectors such as industrial manufacture, agricultural production, access to water, education, health, population, life quality, etc., (Suganthi and Samuel, 2012). For an efficient management of energy, industry and governments must concurrently follow these three issues (S´anchez-Dur´an, Luque, and Barbancho, 2019):

- Energy security (consistency of energy infrastructure, and capability of energy suppliers to fulfill present and upcoming demand),

- Energy equity (availability and affordability of energy supply for the population),
- Environmental sustainability (energy productivity and the improvement of energy provided by renewable and other low-carbon sources).

It is estimated that industrial sectors account for over 50% of global energy consumption (Safarian, 2023). Moreover, it is reported that the annual consumption of energy in the Organisation for Economic Co-operation and Development (OECD) countries have risen by 0.5%. In comparison, this amount for non-OECD countries has expanded by about 1%. Moreover, from 2006 to 2030, energy utilization in the industrial section (non-OECD and OECD countries) grew by about 1.4% per annum (U.S. Energy Information, 2020).

On the one hand, fossil fuel sources including coal, oil, and natural gas have been the main energy sources in energy production for a long time. While the share of natural gas has been increasing, the share of coal and oil has been gradually decreasing (British Petroleum-BP, 2022; Energy Information Administration-EIA, 2022). It is observed that fossil fuels provide more than 80% of the total energy supply, while renewables account for only 20% (Zakari et al. 2021). On the other hand, renewable energy sources have been used in energy production since 1965. In this group, geothermal, biomass, and hydro are the leading sources whereas other renewable sources are wind and solar (Depren et al. 2022).

Renewable energy, while undoubtedly a preferred source of energy, can replace fossil fuels but not in the short term. A full transition from fossil fuels to renewable, clean energy will not happen overnight. It is not an easy task for policymakers to restructure the existing energy production structure from fossil fuel sources to renewable sources because of environmental concerns. (BP, 2022; Oliveira and Moutinho, 2021). Fossil fuels are extraordinarily energy dense, and it is easy to generate energy from fossil fuels and — more importantly — to capture the energy produced during fossil fuel combustion. Fossil fuels are a stable and non-toxic energy source relative to most other proven energy sources. Additionally, fossil fuels are stable and non-toxic that is safe to use in public highways and thoroughfares as well as cargo ships to transport fossil fuels. Additionally, concerning providing renewable energy, for instance, each wind turbine needs 260 tonnes of steel created from 170 tonnes of coking coal. Similarly, while no emissions come directly from an electric car, they cannot operate without power generated using fossil fuels like coal and natural gas that generate emissions. Therefore, the world still needs fossil fuels for utilization of renewable energy.

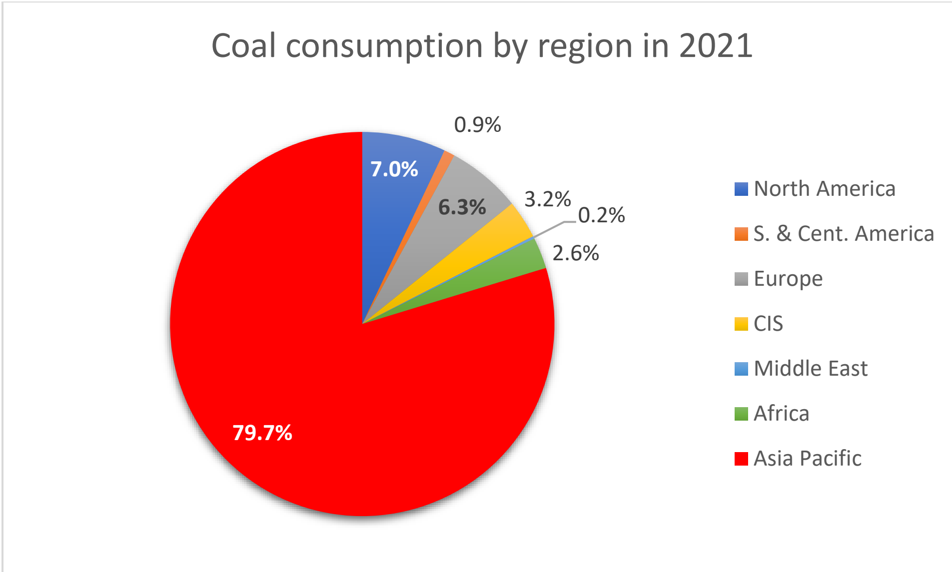

Fig.1.1. Coal consumption by region in 2021

1.2. Coal SC

Among fossil fuels, coal is a key fundamental energy source, and has a critical position in stabilizing national economies (Kang et al., 2014). Almost all coal is composed of dead plant material. As a result of accumulated plant material being buried under anoxic conditions for millions of years and being exposed to high temperatures and pressures over that time, coal was formed (Australian Government, 2022). Coal is the world's greatest sole source of electrical energy (37%) and will continue the most significant supplier (22%) until 2040. Moreover, coal aids non-energies manufacturing such as cement, steel (70%), and aluminium production (60%), rare earth element extraction, coal-to-chemicals, carbon fibre manufacture, and industrial electrodes (World coal association). Typically, about 630kg of coal are demanded to produce one metric ton of steel (Corsa). To produce one ton of cement, approximately 200-450kg of coal is required and about 20% of hydrogen production occurs by coal-to-gas processes (World coal association). In Fig. 1.1, global coal consumption by region in 2021 is presented (Statistical Review of World Energy, 2021). About 75% of coal is found in only five countries (USA, Russia, Australia, China, and India), while the biggest coal consumers are China (54%), India (18%), USA (6%), Japan (3%), and South Africa (2.3%) (Phengsaart et al., 2023). According to Notes from Poland (2022), Poland ranks 9th in the world in coal consumption to generate 70% of electricity, by far the highest figure in Europe. In terms of production, China tops the list supplying about 50% of global coal demand. Other key players in the global coal trade include India (9.9%), Indonesia (7.5%), USA (6.4%), Australia (5.9%), Russia (5.3%) and Poland (1.3%) (Phengsaart et al., 2023).

Iran (Persia), in Southwest Asia with an area of 1.64 million square kilometres (0.63 million square miles), is the 17th-largest country in the world. Iran has an estimated population of 86.8 million, making it the 17th-most populous country in the world, and the second largest in the Middle East. Iran is the fifth richest country in the world in terms of natural resources such as oil, gas, coal, wood, gold, silver, copper, uranium, crude iron, and phosphate. With one percent of the world's population, it has more than 7 percent of the world's mineral resources. In terms of energy, Iran was the fifth-largest crude oil producer in OPEC in 2021 and the third-largest natural gas producer in the world in 2020. Iran is also the fourth richest country in the world in terms of fossil fuel reserves. It holds some of the world's largest deposits of proved oil and natural gas reserves, ranking as the world's third-largest oil and second-largest natural gas reserve holder in 2021. At the end of 2021, Iran accounted for 24% of oil reserves in the Middle East and 12% in the world (EIA, 2022). With these huge amounts of fossil fuel reserves, Iran is considered an "energy superpower".

Fig. 1.2 Coal mines in Iran (Zadehkabir, 1992)

With about 1.15 billion tons of reserves (ranking 29th in the world), Iranian coal mines can deliver up to three million tons of coal concentrate yearly (IEA, clean coal centre, 2020). The coal-bearing deposits of Iran are spread throughout the central, northern and northwestern regions of the country, and occupy a vast area of some 100 thousand sq.km (Zadehkabir, 1992). Due to the presence of high oil and natural gas reserves in Iran, thermal coal mines are not considered properly. In contrast, steel manufacturers in Iran (and worldwide) have a considerable demand for coking coals because it is one of the essential unique inputs for steel production employing blast furnaces (Mohanty et al., 2019). Coking coal, also named metallurgical coal, is a type of non-renewable resource, and it is mainly intended for making coke, a coal-based fuel. For instance, in 2019, the coal utilisation in the steel sector was around 900 million tons of coal equivalent (Mtce) (26.2 exajoules [EJ]) or about 15% of the initial international coal demand (Iron and Steel

Technology Roadmap). The Tabas Parvadeh Coal Company (TPCCO), located in Tabas city, is the biggest coal producer in Iran. Consistent with the statistics published by the Iranian Mines and Mining Industries Development and Renovation Organization (IMIDRO), TPCCO extracted 1.232 million tons of coal from March 21, 2019, to January 20, 2020). Almost the majority of these amounts were bought by steel companies in Iran.

1.3. Energy and environmental issues

On the one hand, energy is essential for economic growth; however, energy consumption also negatively influences long-term economic progress by adversely affecting environmental quality and human welfare in the developing world. Developing countries strive to become more advanced, which increases their energy consumption (Chen et al. 2023). On the other hand, reducing energy utilization is crucial for environmental protection and developing sustainable resources (Jawad et al., 2018).

An issue that could impact heavy industry SCs, such as steel, cement, and coal power plants, is that these industries form a massive percentage of carbon dioxide (CO_2) emissions (Sun and Yang, 2021). Coal's primary gas emissions, such as CO_2, SO_2, NO_X, and smoke dust, can contribute to global warming, damaging the ozone layer and creating acid rain (Manisalidis et al., 2020). Iron and steel manufacturing, for instance, emitted about 2,600 million tons of carbon in 2019. This number is expected to rise to 2,700 million tons by 2050 if no sustainable development scenario is applied (U.S. Energy Information Administration (EIA), 2022). As society becomes more aware of the value of the environment, waste disposal (imperfect quality items) and carbon dioxide emissions must become leading indicators of coal SC assessment (Mehmood et al., 2015). According to the European Union's Joint Research Centre, China is the largest emitter of CO2 in the world, with 11680 Mt (11.680 GT) of carbon dioxide emissions in 2020. This is just over 32% of the world's total 2020 emissions. The United States and India released the second- and third-highest amount of carbon emissions at 4.535 and 2.411 GT (or roughly 12.6% and 6% of total global emissions). Moreover, Japan and Iran are the 5th and 6th CO2-emitting countries in the world. It should be mentioned that China, the USA, and India are also three of the most populous countries on Earth. In general, developed countries and major emerging markets lead in total carbon dioxide emissions.

Various countries worldwide set impressive emission reduction goals for the future to tackle climate change and for sustainable development (Malladi and Sowlati, 2020; Sun and Yang, 2021). In this effort, environmental administrations around the globe agree that pricing carbon emissions are the inexpensive and most successful means to achieve their emission reduction goals (Environment and Climate Change Canada, 2018). The primary carbon pricing strategies are carbon tax, carbon cap, carbon offset, and carbon trade (Malladi and Sowlati, 2020), whereas each carbon strategy has different costs and carbon reductions. The benefits of applying each carbon emission policy are not equal for companies involved in coal SC. While some carbon policies are more environmentally friendly, others are more economically beneficial.

1.4. Sustainable SC and Extended Exergy Accounting (EEA) method

SCs are the operational sequence of interconnected procedures that manage, plan, and control goods and services between buyers and vendors (Roozbeh Nia et al., 2020). Besides the monetary costs of a coal SC, for instance, miners, washing factories, shippers, and power plants/steel producers, there are other charges known as "hidden costs" associated with environmental influences and emissions. Both costs should be considered in the entire operational costs of the coal SC (Phillips, 2008). Any manufacturing process that reduces "hidden costs," for instance, environmental effects, is recognized as a sustainable procedure. Sustainable SC is the administration of material, information, and assets streams in addition to teamwork among corporations alongside the SC whereas choosing objectives from entirely three elements of sustainable progress, namely, environmental, economic and social, which are come from customer and shareholder necessities (Asadi and Sadjadi, 2017; Bui et al., 2020; Mangla et al., 2017). A sustainable SC is designated by a company's ability to decrease the consumption of energy, materials, or water and to discover solutions that are further eco-efficient by enhancing the administration of their SCs. Sustainable SC management is the improved level of management through the integration of environmental and social issues in parallel to the economic issues (Jawad et al. 2018). More precisely, sustainable SC management must be expressed to fulfill the necessities of the existing generation of businesses without failing the capability of forthcoming generations (for example, Industry 4.0) to accomplish their needs (Jabbour et al., 2020).

Moreover, emerging Industry 4.0 technologies and concerns about global warming show that decision-makers need to change their point of view in assessing the SC's performance (Roozbeh Nia et al., 2020). Shifting from traditional assessment methods to novel and more sustainable methods is one of the critical aspects of the fourth industrial revolution. Extended Exergy Accounting (EEA) is an innovative method that can help SCs become more sustainable (Aghbashlo et al., 2018). This method integrates the effect of non-energetic manufacturing features into the complete loss assessment (Jawad et al., 2018; Sciubba, 2011). EEA is the quantity of initial exergy (in Joules; J) aggregate consumed in the manufacture, operation, and discarding procedure of certain goods or services. In this thesis, exergy is considered as the maximum useful work that can be obtained when a system is brought into stability with its surroundings by means of a reversible process (Jawad et al. 2015). It means, Exergy is that portion of Energy available to do work (Robinett et al., 2006). The EEA delivers more information than an entirely financial method, which cannot support any suggestion about utilizing global resources (Jawad et al., 2016). The initial aggregate exergy includes material (*M*), and energy (*E*), corresponding exergy of labor (*L*), money (*Cap.*), and ecological (*Env.*) remediation costs, of which the last three components are counted as the cost correspondence of economic externality and ecological externality (Song et al., 2019).

The primary benefit of employing the EEA method in the production system is that this method states all outcomes in Joules (instead of dollars); therefore, acceptable assessments among different products can be achieved (Naderi et al., 2021b; Jawad et al., 2018). Moreover, energy (in terms of Joules) is essential to operate all manufacturing and SC processes (Jawad et al., 2015). The EEA has been widely accepted as a comprehensive metric that accounts for both physical and monetary costs associated with the consumption of primary resource. The EEA over traditional exergy analysis has the advantage of connecting the technical production process of specific produces as well as production processes with their surrounded system, such as social system and surrounding Environment (Song et al., 2019). As a result, the EEA refers to a broad "value measure” for “environmental cost formation” in terms of investments and loses of the complex system of society-economy-environment comprising Material and Energy resources, Labor force (L), and Capital (Cap), in addition to Environmental remediation costs (Env.). The EEA gives more information than an entirely monetary method, which is unable to support any indication about the consumption of global resources (Jawad et al. 2016). Consequently, the companies can match the amount of the manufactured product with the needed resources to reach the preferred level of sustainability. Therefore, EEA can facilitate an understanding of the environmental costs from a comprehensive and multidimensional perspective, which bridges the gap about the ‘production of value’ and distinguishes most economics and biophysical based methods (Dai et al. 2012).

Based on Sciubba (2011), the EEA method determines the exergy corresponding to Labour, Money, and Ecological remediation in goods or services by elements of “α” and “β” and some financial factors like GDP. These aspects are highly inspired by population, labor statistics, regular and international income, and normal workload. The stated aspects and exergy counterparts were examined and analyzed by Sciubba (2011) for some developed and developing countries.

1.5. Research Gaps

In earlier studies, as we will see in the literature review section, the meaning of SC costs was workflow-associated, as opposed to exergy costs. Although other studies have considered exergy costs, few have considered all aspects (labour, capital, and environmental remediation) simultaneously (like the EEA method) on a scale of SC. Additionally, no research has examined the EEA method and carbon reduction policies in SC. Carbon policy and sustainable SC have now recognized fields of research that consider many distinct aspects, such as resource consumption, source destinations, and waste-related hidden costs.

Despite this, there are still several research gaps, including the following:

G1. There is a lack of research that assesses a SC under any carbon reduction policy within an uncertain environment, for example, carbon price or customer demand.

G2. It is rare to find studies that assess a SC in terms of Joules instead of dollars (as a traditional performance measures) and simultaneously evaluate all sustainability aspects, such as economic, labour, and environmental.

G3. There is a lack of studies that employ the EEA method to assess a SC under any carbon reduction policy. As a matter of fact, no exergy analysis method in the literature takes into consideration a carbon emission policy.

G4. There is a scarcity of studies that compare the sustainability of coal SCs between developed and developing countries under carbon policy with the EEA method.

G5. There is a deficiency of investigation to find the best percentage of exergy components (social, economic, environmental aspects) in the EEA method for a SC.

G6. In addition, some real-world issues are ignored, such as considering the inventory turnover ratio for SC models, defective quality products discarded into the environment, shipping charges on the whole of SC, vendor managed inventory (VMI) policy for coordinating SC, and the costs of loan/investment due to budget limitation.

1.6. Research Questions

The functioning of the entire coal SC is one of the critical interests to concerned stakeholders (Mehmood et al., 2015). As society increasingly recognizes the value of the environment, waste disposal and carbon emission must become two of the leading indicators of coal SC assessment. Additionally, employing different carbon pricing strategies results in various costs and carbon reductions in SC. Moreover, as we will see in the literature review section, the number of publications employing the EEA method is insufficient. Additionally, to the best of the authors' knowledge, no study considers carbon reduction policies with the EEA method (or exergy analysis) at the same time in a coal SC. Therefore, we can present four main research questions as follows:

Q1. Does incorporating a carbon reduction strategy with the EEA method in coal SC trigger financial benefits and sustainability advantages?

Q2. The coal SC in developing countries is supposed to have the lowest cost overall; however, in terms of sustainability (social, economic, and environmental aspects) and considering Joules rather than monetary objectives, does this assumption remain accurate?

Q3. Which country has the most sustainable coal SC in terms of Joules?

Q4. What is the best percentage of exergy components (social, economic, environmental characteristics) to achieve the most significant saving wherever coal SCs are working?

1.7. Research contributions

This study aims to extend Jawad et al. (2016) and Naderi et al. (2021a) into a multi-product, multi-limitation EOQ/EPQ model with backorder for a coal SC in Iran under an uncertain environment. A VMI contract is used between a single supplier and multiple buyers to coordinate a coal SC. By utilizing the EEA method and Joules as a unit of inventory cost, we can estimate the total exergy of coal SC. Four famous carbon reduction policies (carbon cap, tax, trade, and offset) are employed to compare the model's performance as a sustainability measure and restrict the produced carbon emissions of SC enterprises. To minimize the fuzzy total exergy of coal SC, some recent metaheuristic algorithms are applied to obtain a near-optimal solution to the exergy fuzzy nonlinear integer programming (EFNIP). In addition, some numerical examples, including an actual case study in a coal SC in Iran, were used to demonstrate the usefulness of the proposed models. Additionally, the results of the metaheuristic algorithms are compared with the results of the exact method (GAMS). In order to gain a deeper insight into the sustainability of coal SC in various developed and developing countries, a sensitivity analysis with changing the percentages of various exergy parameters (capital, labour, and environmental remediation) under each carbon policy for each country has been performed. We are looking for the optimal balance point (financial and sustainable) in terms of total exergy for each country's coal facilities. This study contributes the following to the literature:

- Improving the sustainability of coal SCs in terms of Joules (total exergy rather than traditional monetary objectives) in developed and developing countries under different carbon policies and the uncertain environment by employing the EEA method.

- Comparing the sustainability of coal SC in different countries to determine which country has the most sustainable coal SC in terms of Joules.
- Finding the best value of exergy components (social, economic, environmental characteristics) for coal SC in both developed and developing countries which creates the highest sustainability.

The remainder of this manuscript-based thesis is structured as follows. The method of reviewing research works of the past two decades is described in Chapter 2. Moreover, in Chapters 3 and 4 (two published papers), a comprehensive literature review of past two decades in “Management of Sustainable Supply Chain and Industry 4.0” and “Industry 4.0 and demand forecasting of the energy supply chain” are presented. After that, improving the sustainability of coal SC in both developed and developing countries by incorporating extended exergy accounting and carbon tax policy (in Chapter 5-Third published paper) and carbon trade policy (in Chapter 6-Fourth published paper) are stated. Additional results for carbon cap policy and carbon offset policy are presented in Chapters 7 and 8, respectively. Finally, conclusions and potential studies are offered in Chapter 9.

CHAPTER 2. LITERATURE REVIEW

In this chapter, the research works of the past two decades is reviewed based on the arrangement. Moreover, a comprehensive literature review will be presented in Chapters 3 and 4 by two journal publications.

2.1 Method of reviewing

A comprehensive online exploration of related research works in coal SC is presented here. This exploration aims to gather, classify, and synthesize current exergy analysis and carbon reduction policies in SC. Thomson Reuter's Web of Science is used to review the literature for 2000-2022. We attempted to sort publications by reviewing their titles, abstracts, and texts in the absence of precise keywords. Following is an overview of the general review methodology:

Step 1- Finding the sources (online databases)

Step 2- Searching key words

Step 3- Developing a taxonomy and analysis based on journal papers, conference papers, books, and theses.

Step 4- Identifying research with implications and issues related to exergy, sustainability, supply chain, coal, and carbon policies.

Step 5- Presenting survey outcomes.

Our initial search strategy was to use keywords such as "Exergy" in Thomson Reuter's Web of Science's "TOPIC" search field. More than 20111 articles were found to be unrelated to our objectives after investigation. Our search was refined to include the keywords of "Exergy" and "Supply chain" in the "TOPIC" field, and we obtained 125 articles. There were nine publications by adding "Coal" to the previous keywords while adding "Carbon" resulted in only two publications. In order to refine the search more precisely, we substituted "Extended Exergy Accounting" with "Exergy," along with "Supply chain," and we found only seven publications. Furthermore, entering "Carbon policy" or "Coal" as keywords does not yield results. Table 2.1 displays all search results.

Table 2.1. keywords search for exergy publications

Keywords (2000-2022)	Number
Exergy (Topic)	20111
Exergy (Topic) AND supply chain (Topic)	125
Exergy (Topic) AND supply chain (Topic) AND Coal (Topic)	9
Exergy (Topic) AND supply chain (Topic) AND Coal (Topic) AND Carbon (Topic)	2
Exergy (Topic) AND supply chain (Topic) AND Coal (Topic) AND Carbon (Topic) AND sustainable OR sustainability (Topic)	2

Exergy (Topic) AND supply chain (Topic) AND Coal (Topic) AND Carbon policy (Topic) AND sustainable OR sustainability (Topic)	1
Extended Exergy Accounting (Topic)	138
Extended Exergy Accounting (Topic) AND supply chain (Topic)	7
Extended Exergy Accounting (Topic) AND supply chain (Topic) AND Coal (Topic)	0
Extended Exergy Accounting (Topic) AND supply chain (Topic) AND Carbon (Topic)	2
Extended Exergy Accounting (Topic) AND supply chain (Topic) AND carbon policy (Topic)	0

We divided the keywords into two sections since no publication considers all keywords. Thus, we conducted a second search with "Carbon policy," "Supply chain," and "Coal," resulting in 78 publications, whereas adding "Sustainability" or "Sustainable" to them will decrease the numbers to 30. We further refined our search using specific carbon policy keywords such as "carbon tax," "carbon trade," "carbon cap," and "carbon offset." Table 2.2 shows all the results in detail.

Table 2.2. keywords search for carbon policies publications

Keywords (2000-2022)	Number
Carbon (Topic) AND supply chain (Topic)	5412
Carbon (Topic) AND Coal (Topic) AND Supply chain (Topic)	240
Carbon (Topic) AND Coal (Topic) AND Supply chain (Topic) AND sustainable OR sustainability (Topic)	73
Carbon policy (Topic) AND Coal (Topic) AND Supply chain (Topic)	78
Carbon policy (Topic) AND Coal (Topic) AND Supply chain (Topic) AND sustainable OR sustainability (Topic)	30
Carbon cap (Topic) AND Coal (Topic) AND Supply chain (Topic)	8
Carbon cap (Topic) AND Coal (Topic) AND Supply chain (Topic) AND sustainable OR sustainability (Topic)	5
Carbon tax (Topic) AND Coal (Topic) AND Supply chain (Topic)	10
Carbon tax (Topic) AND Coal (Topic) AND Supply chain (Topic) AND sustainable OR sustainability (Topic)	4
Carbon trade (Topic) AND Coal (Topic) AND Supply chain (Topic)	59
Carbon trade (Topic) AND Coal (Topic) AND Supply chain (Topic) AND sustainable OR sustainability (Topic)	11
Carbon offset (Topic) AND Coal (Topic) AND Supply chain (Topic)	12
Carbon offset (Topic) AND Coal (Topic) AND Supply chain (Topic) AND sustainable OR sustainability (Topic)	4

2.2. Literature review

A complete literature review of management of sustainable SC is done in Chapter 3. Moreover, Chapter 4 presents a comprehensive and up-to date review of publications related to forecasting approaches of energy demand in the last two decades between 2000 and 2020 related to the energy SC (coal, oil, etc.). Furthermore, Chapters 5 and 6 (subsection 5.2 and 6.2) present a complete review of research works related to exergy analysis and carbon reduction policies.

Chapter 1
Management of Sustainable Supply Chain and Industry 4.0: A Literature Review

Ali Roozbeh Nia, Anjali Awasthi, and Nadia Bhuiyan

Abstract This review aims to investigate the advanced collected works on sustainability and Industry 4.0 in the supply chain (SC) management from both academic and industrial standpoints. Hence, a review of the literature from 2010 to 2018 has been presented, knowledge gaps and all areas of application in the assumed investigation topic are highlighted, and the key features of the former study are associated. Furthermore, a dynamic framework for this topic is proposed consistent with the benefits, drawbacks, and boundaries of current research works, and the term "Sustainable Supply Chain 4.0" (SSC 4.0) is proposed. The suggested dynamic framework aims to distinguish the characteristics, elements and technology enablers, achievement aspects and challenges for evolving an SSC 4.0. Therefore, the current study and dynamic framework can provide awareness to academics and industrial specialists in their application of SSC 4.0.

Keywords Supply chain (SC) · Sustainable supply chain 4.0 (SSC 4.0) · Literature review · Industry 4.0 · Sustainability

1 Introduction

Traditional supply chains (SCs) comprise tangible facilities distributed with respect to geography support, create, and sustain shipping connections among them. SCs are explained in the functional chain of interrelated actions that include the direction, scheduling, and checking of services and goods among clients and providers (see Fig. 1). These managerial configurations are no more independent as a result of industrial progress (Büyüközkan and Göçer 2018). There are some factors which influence SC management such as performance, technology, environmental policy,

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CHAPTER 3. PAPER ONE - MANAGEMENT OF SUSTAINABLE SUPPLY CHAIN AND INDUSTRY 4.0: A LITERATURE REVIEW

Forewords

After reconsidering the method of literature review in Chapter 2, in this Chapter and Chapter 4 (two published papers), a comprehensive literature review of past two decades in "Management of Sustainable Supply Chain and Industry 4.0" and "Industry 4.0 and demand forecasting of the energy supply chain" are presented. Moreover, in subsection 5.2 and 6.2 (Chapters 5 and 6) a complete review of research works related to exergy analysis and carbon reduction policies are presented.

Abstract

This review aims to investigate the advanced collected works on sustainability and Industry 4.0 in the supply chain (SC)management from both academic and industrial standpoints. Hence, a review of the literature from 2010 to 2018 has been presented, knowledge gaps and all areas of application in the assumed investigation topic are highlighted, and the key features of the former study are associated. Furthermore, a dynamic framework for this topic is proposed consistent with the benefits, drawbacks, and boundaries of current research works, and the term "Sustainable Supply Chain 4.0" (SSC 4.0) is proposed. The suggested dynamic framework aims to distinguish the characteristics, elements and technology enablers, achievement aspects and challenges for evolving an SSC 4.0. Therefore, the current study and dynamic framework can provide awareness to academics and industrial specialists in their application of SSC 4.0.

Keywords Supply chain (SC); Sustainable supply chain 4.0 (SSC 4.0); Literature review; Industry 4.0; Sustainability

3.1. Introduction

Traditional supply chains (SCs) comprise tangible facilities distributed with respect to geography support, create, and sustain shipping connections among them. SCs are explained in the functional chain of interrelated actions that include the direction, scheduling, and checking of services and goods among clients and providers (see Fig. 3.1). These managerial configurations are no more independent as a result of industrial progress (Büyüközkan and Göçer 2018). There are some factors which influence SC management such as performance, technology, environmental policy, economics, SC collaboration, competition, strategy, customer engagement, real-time information, procurement, and zero errors (Manavalan and Jayakrishna 2019).

On one hand, several companies take on uncertainty because of an increasing marketplace demand for different goods and services at the end of the twentieth century. On the other hand, economically beneficial types of manufacture cause durable influences on the environment and civilization (Rajeev et al. 2017). Therefore, the combination of economic with social and environmental concerns, or sustainability, must be a shared interest among researchers and practitioners (Brandenburg et al. 2014; Seuring and Müller 2008). Progressively, environmental problems were used as a basis for strategic transformation (Aragón-Correa et al. 2008). Recently, environmental aspects attract many researchers in the literature (Roome, and Hinnels 1993; Noci and Verganti 1999; Schiederig et al. 2012). In addition, eco-innovation methods such as life cycle valuations, cleaner manufacture, and eco-design are employed in many companies (Huber 2008; Van Hemel and Cramer 2012).

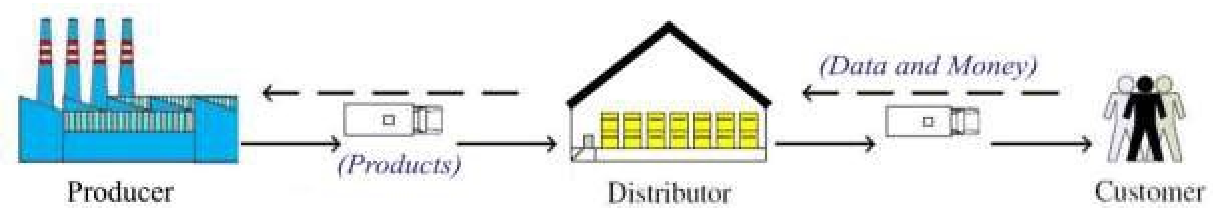

Fig. 3.1. An illustration of a traditional supply chain (Roozbeh Nia et al. 2014)

The management of sustainable supply chains (SSC) is described by Seuring and Müller (2008) as "the administration of substance, information and assets streams in addition to teamwork among corporations alongside the SC whereas choosing objectives from entirely three elements of sustainable progress, namely, environmental, economic and social, which are come from client and shareholder necessities". For about 20 years, the issue of SSC has been given significant attention by researchers and specialists (Craig and Easton 2011; Beske et al. 2014; Brandenburg et al. 2014; Ghadimi et al. 2016, 2019; Seuring and Müller 2008; Seuring 2013). SSC management is fundamentally a part of green supply chain management (GSC), that is, the combination of ecological philosophy in the management of SC (Srivastava 2007) which encompasses environmental, economic, and social interests (Yan et al. 2016). An SSC is designated by a company's ability to decrease the consumption of energy, substances, or water and to discover solutions that are further eco-efficient by enhancing the administration of their SCs (Lopes de Sousa Jabbour et al. 2015).

Nowadays, most initiatives are undergoing digitization Industry 4.0. The emphasis of the digital revolution is placed mostly on manufacture; consequently, the names for instance "Smart Factory" or "Factory of the Future" are employed and compared with this idea (Kayikci 2018). In 2011, the German association "Industrie 4.0" invented the term Industry 4.0. The association is made of managers, academics, and legislators, who suggested a fourth industrial revolution is created on the digitization of organization procedures (Kagermann et al. 2011). In fact, the key impression motivating Industry 4.0 is to guide companies by implementing digital technologies that know how to assist in generating links among their process, provide systems, manufacturing capabilities, finished goods, and clients with the purpose of collection, and distribute real-time functioning and marketplace information with stakeholders (Ardito et al. 2019). The digitization in SCs is established based on six features: connectivity, cooperation, integration, adoption, cognitive improvement, and autonomous control (Kayikci 2018). Furthermore, for Industry 4.0, the empowering technologies include additive manufacturing, advanced manufacturing, augmented reality, cloud computing, simulation, industrial IOT, big data analytics, cybersecurity, and customer profiling (Ardito et al. 2019).

Industry 4.0 has been demonstrated to be successful in offering several business advantages containing operational optimization and value chain optimization (Strange and Zucchella 2017). Accordingly, Industry 4.0 is widely adopted by German companies, for instance, Volkswagen, Daimler, and BMW. In addition, the Government of China has likewise presented the "Made in China 2025" strategy which focuses on enhancing manufacturing through speeding up digitalization in China. Similar plans have also been started by the USA, French, UK, Japanese, and Singaporean governments (Bag et al. 2018). More precisely, the objective of Industry 4.0 is to improve the digitization and, therefore, the combination of business procedures mutually horizontally (that is through functional parts) and vertically (i.e., through the whole value chain, from goods procuring to production, delivery, and customer service). Along these lines, entire data-concerning processes, inbound/outbound logistics, marketplace requirements, and product–customer relations will be accessible in real time. Consequently, digital initiatives will operate jointly with clients and providers in an industrial digital ecosystem that permits them to superior handle the line among SC management and promotion purposes (Schrauf and Berttram 2016; Ranganathan et al. 2011).

There exist several explanations for taking into consideration the digitalization influences in SCs and the significance of SC in Industry 4.0. The main potentials of this idea allow real-time definite from providers to clients, small orders quantity, various goods changes, linked decentralized procedures, and autonomous administration. These advantages cannot be attained just by manufacture besides the whole of SC, though. Furthermore, SCs must achieve a bigger foresight to accomplish the necessities of Industry 4.0 as sustainable and as probable in expressions of using suitable technologies and improving horizontal and vertical combination with the SC associates (Kayikci 2018). SC with Industry 4.0 is transformed into a value-driven, smart, effective procedure to produce novel outlines of income and commercial value for administrations and to influence innovative methods with novel technological and systematic procedures as well. SC within the Industry 4.0 is not about if products and facilities are physical or digital, it is about the manner in what way SC procedures are administered by an extensive diversity of innovative technologies, such as "Big Data" (BD), "Augmented Reality" (AR), "Cloud Computing" (CC), "Sensor Technology" (ST), "Robotics" (R), "Omni Channel" (OC), "Internet of Things" (IOT), "Unmanned Aerial Vehicle" (UAV), "Self-Driving Vehicles" (SDV), "Nanotechnology" (N), and "3D Printing" (3DP), but a few to mention (Büyüközkan and Göçer 2018).

This survey is prepared in this way: the next section reviews and classifies associated publications, in addition to clarifying the methodology assumed in this study. Reviewing the idea of SSC and Industry 4.0, its aspects and elements to shape a dynamic conceptual framework that is resulting from the current literature are represented in Sect. 3.3. In Sect. 3.4, the benefits and challenges of Industry 4.0 for SCs are described. A dynamic framework for SSC and Industry 4.0 is proposed in Sect. 3.5. Finally, the article's concluding remarks, the limitations, as well as possible directions for SSC and Industry 4.0, are presented in Sect. 3.6.

3.2. Review of Literature on SSC and Industry 4.0

This review of earlier research works is built on arrangement procedure which offers in what way the literature is considered to be a foundation for the abstract framework. Primarily, the arrangement used in this study is described and afterward, the procedure of the literature review is presented.

3.2.1. Method of Reviewing

Related research works are detected with the help of a comprehensive online exploration, besides the aim to gather, classify, and synthesize current SSC and Industry 4.0 knowledge. Recognized articles span some sorts of connected fields comprising management, marketing, operations management, industrial engineering, management science, and SC management. Owing to the deficiency of exact keywords describing the issue, we put a considerable attempt to sort papers by studying their titles, abstracts, and texts. Typically, this stage can be accomplished through aiming noticeable journals, books, and conferences. It is not true for SSC and Industry 4.0 because this new topic has appeared only a couple of years ago and associated publication networks are not dispersed yet. The literature is reviewed for the period 2010–2018 by exploring the main databases of scientific and common search engines such as Thomson Reuter's Web of Science, Taylor & Francis online, Elsevier's Scopus, IEEE Explore, Emerald Insight, ProQuest (ABI/INFORM), and Science Direct (Elsevier). We examine and organize the related research works to meet a vision of SSC and Industry 4.0. The overall review methodology for SSC and Industry 4.0 papers is as follows:

Phase1: Identifying the sources (online databases)

Phase2: Search keywords

Phase3: Taxonomy, and analysis based on journal papers, conference papers, books, theses, and so on.

Phase4: Implications and issues include SC, sustainability, Industry 4.0, features, component and technologies, challenges and successes factors.

Phase5: Survey outcomes: a framework for the development and identification of future work.

3.2.2. Academic Literature on SSC and Industry 4.0

Industry 4.0 has commenced obtaining considerable concern from companies throughout the world as it makes greater advantages to many businesses. Our review on Industry 4.0 and SSC literature signifies a gap between the theory and practice in SCs. At present, there exist a restricted number of surveys on Industry 4.0 and SSC. There is also SC focused articles which discuss Industry 4.0 and SSC in expressions of their functions. Based on literature review, 55 areas of application for SSC and Industry 4.0 and their Nomenclature are determined in Appendix Table 3.10. The existing research papers and conference papers related to Industry 4.0 and SSC along with their application areas, method, and objective are classified in detail in Appendix Tables 3.11 and 3.12, respectively. In addition, with the consideration of the highest number of citations, top-ten research-papers and top-three conference papers in SSC and Industry 4.0 are presented in Tables 3.1 and 3.2, respectively.

Recently, Lopes de Sousa Jabbour et al. (2018) recommended a master plan to improve the function of the circular economy (CE) notions in businesses by Industry 4.0 methodologies. They contributed to the literature through presentation on what way diverse Industry 4.0 tools could support CE approaches, and to organizations by directing those tools as a foundation for the policymaking of sustainable operations' management. The key outcomes of their research were as follows: (a) an argument on the equally advantageous connection between Industry 4.0 and the CE; (b) a detailed recognition of the possible influences of smart manufacture equipment to the ReSOLVE model of CE business models; (c) an investigation outline for research on the grouping of CE principles and Industry 4.0 based on the best-related administration principles.

Table 3.1. Top 10 Research papers with the highest number of citations in SSC and Industry 4.0.

Citations	Year	Authors	Objective	Area of application	Publisher
203	2012	Davis et al.	Introducing Smart manufacturing, manufacturing intelligence, and demand-dynamic performance	Networked information-based technologies	Elsevier
170	2014	Gebler et al.	This study represents the first comprehensive assessment of 3DP from a global sustainability perspective	3D technologies	Elsevier
56	2014	Holmström and Partanen	The purpose of this paper is to explore the forms that combinations of digital manufacturing, logistics, and equipment use are likely to take and how these novel combinations may affect the relationship among logistics service providers (LSPs), users and manufacturers of equipment.	Manufacturing and logistics	Emerald
53	2013	Baumers et al.	This article investigated whether the adoption of additive manufacturing (AM) technology can be used to reach transparency in terms of energy and financial inputs to manufacturing operations.	Manufacturing and logistics	Yale University
46	2015	Yue et al.	This paper described the development and character of ICPS. Then, it presented a service-oriented ICPS model.	Information communication technology (ICT)	Elsevier
31	2016	Lom et al.	This paper proposed the conjunction of the Smart City Initiative and the concept of Industry 4.0.	Smart City	IEEE
24	2015	Prause	The paper addressed the research question of how new and sustainable business models and structures for Industry 4.0 might look like and in which direction existing traditional business concepts have to be developed to deploy a strong business impact of Industry 4.0.	E-Residency	Elsevier
24	2017	Prause and Atari	The paper investigated the relationship between networking, organizational development, structural frame conditions and sustainability in the context of Industry 4.0.	Manufacturing and logistics	VsI Entrepreneurship and Sustainability Center
24	2014	Brofman Epelbaum and Martinez	This paper presented a theoretical framework grounded on the Resource-Based View (RBV) of the firm to determine the strategic impacts of the technological evolution of food traceability systems.	Food industry	Elsevier
19	2018	Lopes de Sousa Jabbour et al.	The paper extended the state-of-the-art literature by proposing a pioneering roadmap to enhance the application of CE principles in organizations by means of Industry 4.0 approaches.	Circular economy (CE)	Springer

Table 3.2. Top 3 Conference papers with the highest number of Citations in SSC and Industry 4.0.

Citations	Year	Authors	Objective	Area of application	Publisher
8	2016	Ginige et al.	Developing a notion of context-specific actionable information which enables the user to act with the least amount of further processing.	Agriculture sector	IEEE
4	2017	Tan et al.	Discussing how organizations can investigate and implement techniques for their modern enterprise with a focus on how advanced big data tools can be applied to Quality Analytics for monitoring and improving quality in the electronics industry.	Electronic industry	IEEE
2	2010	Price et al.	Presenting a project structure which has been designed to address these issues using at its core, a digital framework for the creation and management of performance parameters related to the lifecycle performance of thermoplastic composite structures.	Thermoplastic composite structures	Mark A Price

Ginige et al. (2016) established a concept of environmental-precise feasible information which allows the customer to perform with the smallest quantity and more administration. User-centered agriculture ontology was established to change distributed quasi-static information to feasible information. They used "empowerment theory" to make empowerment-oriented farming ways to encourage agriculturalists to act on this information and collected the transaction data to create situational information. This method helps agriculturalists for producing various kinds of yields to meet sustainable agriculture production by means of harvest change.

3.2.3. Published Books on Industry 4.0 and SSC

To the finest of our information, there exist six books that focused on Industry 4.0 and SSC (see Table 3.3). Recently, Abdi et al. (2018) developed manufacturing ideas and further functions than tangible manufacture for a broader industrial value chain integrating external shareholders that include providers of raw matters and pieces, clients, manufacturing service suppliers, cooperating manufacturing companies, and environmental organizations. They highlighted the two advanced concepts of reconfigurable manufacturing systems (RMS) and Industry 4.0 together with their joint progress. They presented disputes of mass-customization and active variations in the SC background by concentrating on advancing novel methods connected to integrity, scalability, and re-configurability at the system level and engineering readiness in names of the practical, and commercial feasibility of RMS. The authors applied decision support systems (DSS) for the collection of families' product and optimizing product-process configuration. Their suggested models were explained across real case studies in applicable manufacturing firms.

3.2.4. Published Book Chapter on Industry 4.0 and SSC

Authors recognized seven book chapters on the issue of Industry 4.0 and SSC which are presented in Table 3.4. Recently, Jirsak (2018) examined the influence of Industry 4.0 revolutions on SC management. The writer offered the results achieved in the investigation of recent essential variations and presented a contrast with a preceding conversion of the paradigm. This chapter suggested a revolution that the business SC system has to go over to re-establish its competitive situation in an era of Industry 4.0. In addition, the chapter offered case study of 3PL (demand planning, production planning, and supply planning) insight about Industry 4.0 founded on detailed meetings performed among the major global 3PLs operating in the Czech Republic.

Table 3.3. Literature Review of SSC and Industry 4.0 (Books).

Year	Authors	Objective	Method	Area of application
2012	Goodship and Stevels	Drawing lessons for policy and practice from all over the world	Review	waste electrical and electronic equipment (WEEE)
2014	Xu	Describing the setup of digital enterprises and how to manage them, focusing primarily on the important knowledge and essential understanding of digital enterprise management required by managers and decision makers in organizations.	Modeling	Digital enterprises
2015	Fiorini and Lin	Providing an overview of current topics in intelligent and green transportation on the land, sea and in flight, with contributions from an international team of leading experts.	Review	Intelligent Transport Systems (ITS)
2016	Kiritsis	This book not only explains in detail what LEAP is and how to use it but also provides LEAP case studies from sectors such as auto manufacturing and offshore engineering.	Case study	Manufacturing and logistics
2017	Handfield and Linton	Addressing the changes that have occurred and are still unfolding at various organizations that are involved in building real-time SCs.	Review	Global economy
2018	Abdi et al.	Developing manufacturing concepts and applications beyond physical production and towards a wider manufacturing value chain incorporating external stakeholders that include suppliers of raw materials and parts, customers, collaborating manufacturing companies, manufacturing service providers, and environmental organizations.	Modeling	Reconfigurable Manufacturing Systems (RMS)

Table 3.4. Literature Review of sustainable SC and Industry 4.0 (Book chapters).

Year	Authors	Objective	Method	Area of application
2010	Ndou and Sadguy	Suggesting that digital marketplaces could provide a viable model for SME networking; however, the successful path toward networking requires harmonization of the digital marketplace business model with SC characteristics.	Modeling	SME networking
2013	Montreuil et al.	Providing insights on the foundations of the Physical Internet that has been introduced as a solution to the Global Logistics Sustainability Grand Challenge of improving by an order of magnitude the economic, environmental and social efficiency and sustainability of the way physical objects are moved, stored, realized, supplied and used across the world.	Modeling	Physical Internet
2013	Kückelhaus et al.	Addressing how visibility solutions based on Digital Product Memories (DPMs) developed in the SemProM project can be demonstrated in the logistics domain to guarantee the carbon offset of transport and integrity control within SCs	Modeling	SemProM project
2015	Kagermann	Discussing the impact, challenges, and opportunities of digitization and concludes with examples of recommended policy action.	Modeling	Digitization
2015	Kamarulzaman and Eglese	Providing relevant e-procurement solutions with respect to the MPOI and will provide comprehensive purchasing activities of different types of products along the SC through e-procurement technologies.	Case study	E-procurement technologies

2017	Meera et al.	Proposing a framework for rice extension strategies that integrate knowledge, technology, and markets which helped to provide better, faster, and cheaper solutions to reach out to rice farmers and integrate knowledge, technologies, and markets.	Modeling	Agriculture sector
2017	Kasemsap	Introducing the roles of Lean Supply Chain Management (SCM) strategies and green SCM strategies in the global business environments	Modeling	Global economy
2018	Jirsak	Presenting an impact of Industry 4.0 transformation on logistics and SC management.	Case study	Global 3PLs operating

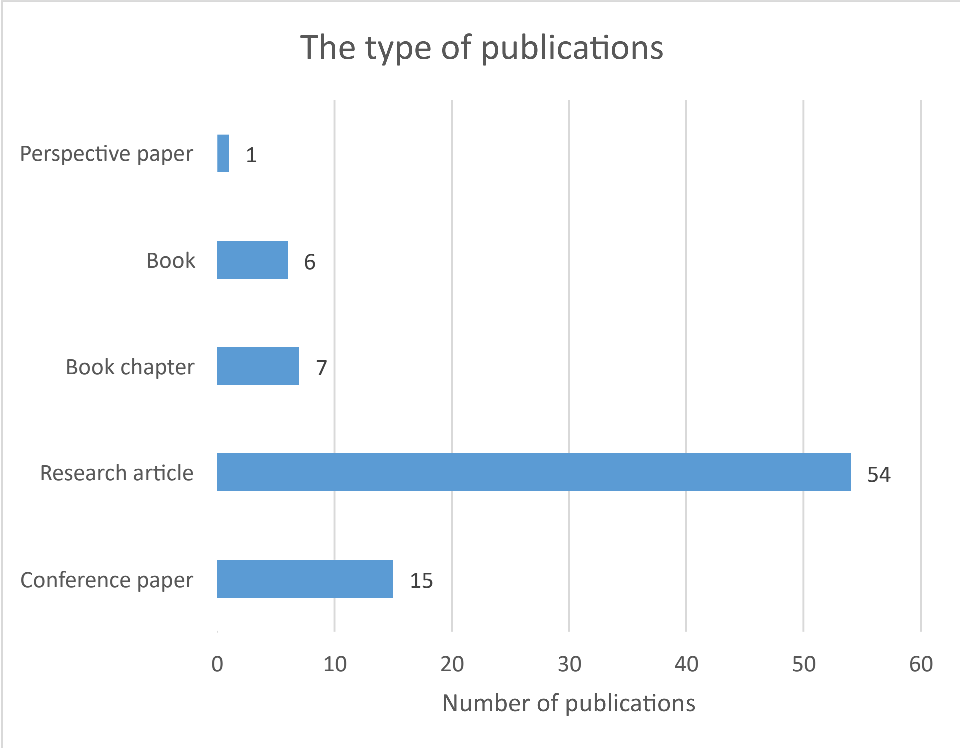

Fig. 3.2. Types of publications for SSC and Industry 4.0.

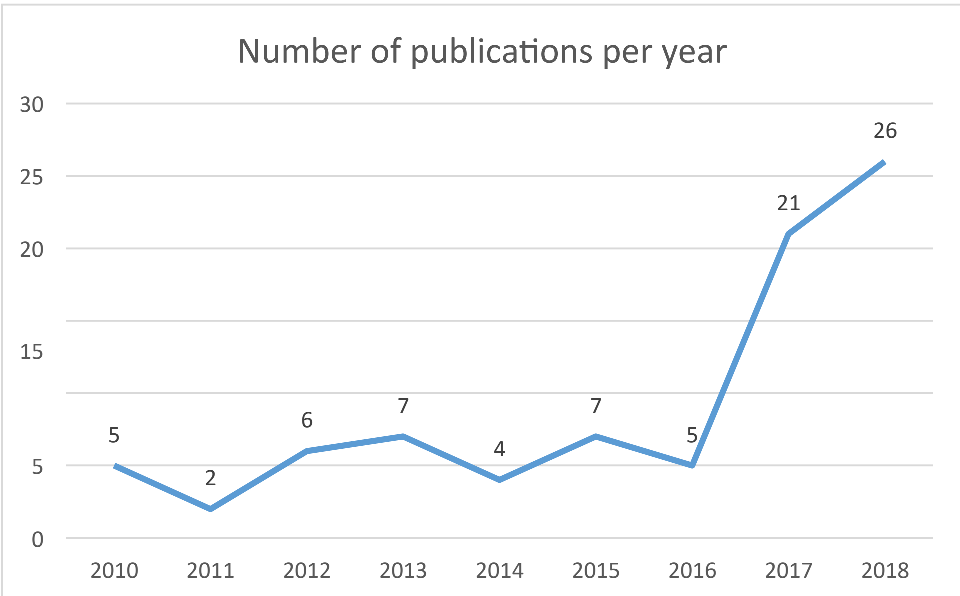

Fig. 3.3. The number of publications for SSC and Industry 4.0 per year.

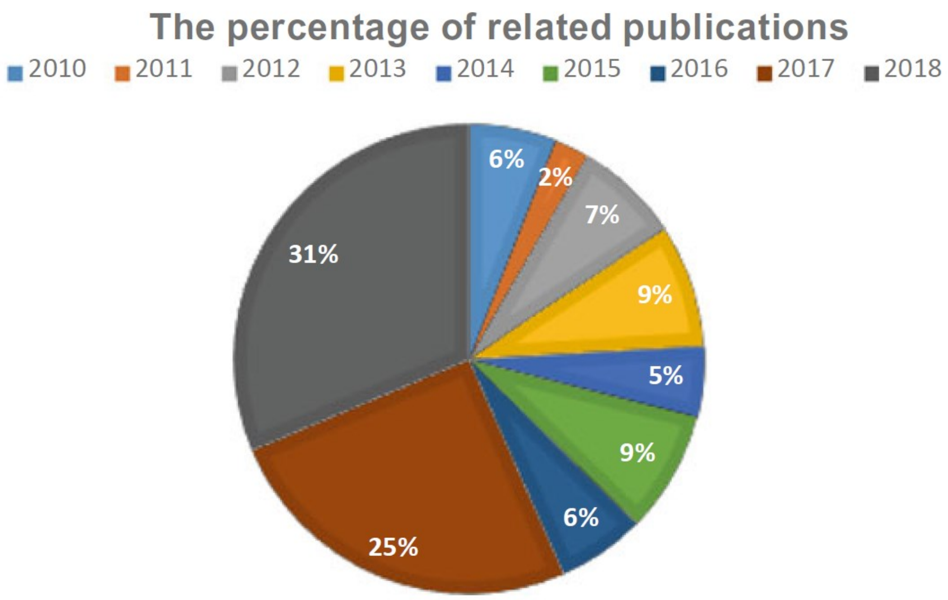

Fig. 3.4. The percentage of publications for SSC and Industry 4.0 per year.

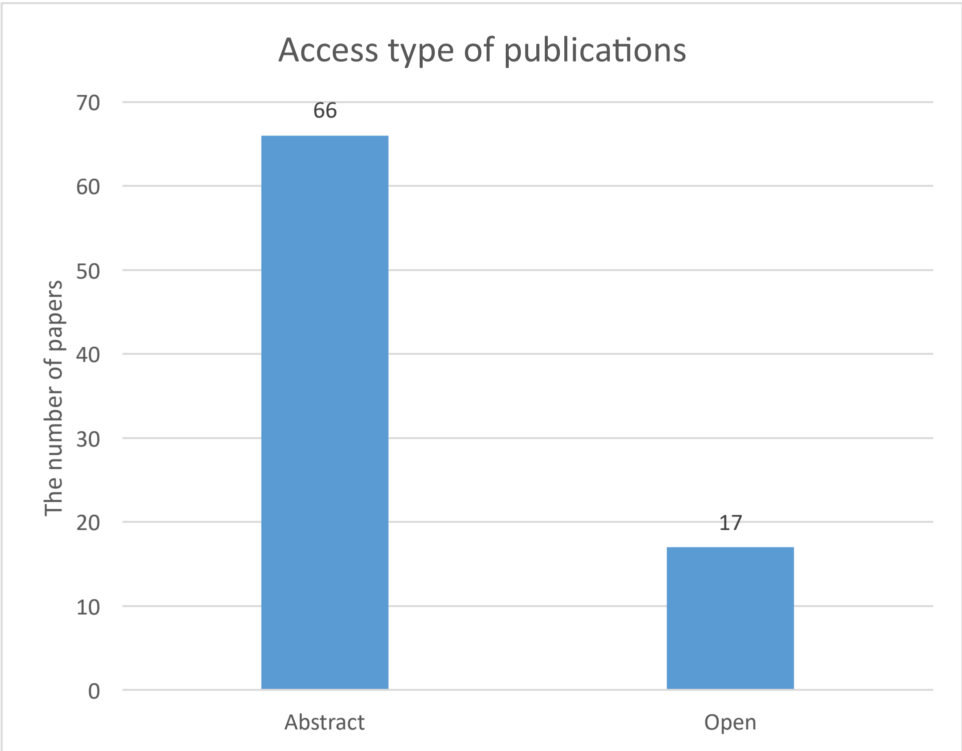

Fig. 3.5. The type of access for publications in SSC and Industry 4.0.

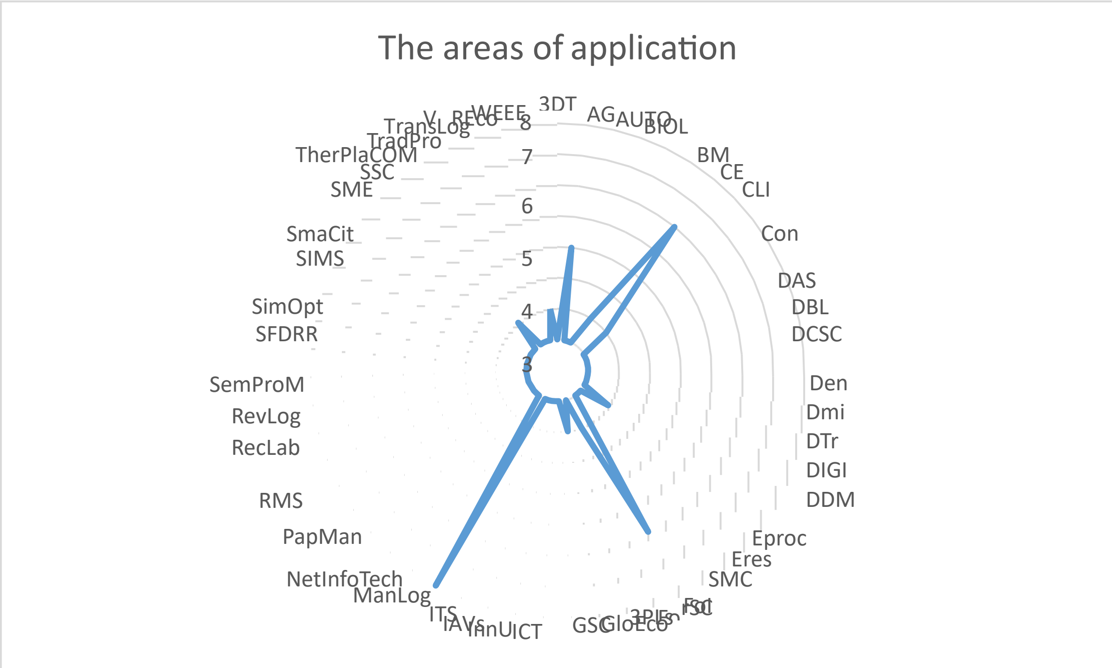

Fig. 3.6. The areas of application for SSC and Industry 4.0.

3.2.5. Analysis of Industry 4.0 and SSC Literature

It is vital to emphasize that the recognition of 83 research works motivated the outcomes of this review, which are informed in Sects. 3.2.2, 3.2.3 and 3.2.4. (Also see the appendix for detailed information.) The keywords were not prearranged ahead of the search; however, they have progressively appeared through the wide-ranging reading procedure that happens during the preparation of this paper. The last list of keywords is as follows: Sustain, Sustainable, Sustainability, Green, Industry 4.0, Smart factory, Digital, Supply chain, and Logistic. In a few conditions, the research under review will still be used to explain the outcomes and meet an improved comprehension of the subject. Figure 3.2 demonstrates the important results by offering a complete sum up in phrases of types of SSC and Industry 4.0 publications. The highest amount of publication was in the form of "research article" with about 45 papers, and the second highest level belongs to "conference paper" with 15 papers. "Book chapter" and "Books" were at the lowest level with 7 and 6 papers, respectively. In addition, the trend for a number of related publications per year from 2010 to 2018 is presented in Fig. 3.3 and the percentage of publications per year is demonstrated in a pie chart in Fig. 3.4.With regard to these figures, the number of publications has a small fluctuation between 2010 and 2016 (about 2–7 papers or 2–9%), while the trend increased dramatically in 2017 to hit the highest point in 2018 with 26 papers (or 31%) out of 83. Moreover, in total, about 17 papers out of 83 were open access and 66 papers have access as an abstract only (see Fig. 3.5). It has been mentioned that we find out about 55 areas of application in SSC and Industry 4.0 literature (see Appendix Table 3.10). Furthermore, we recognized top-five areas of application in the literature (see Table 3.5 and Fig. 3.6) that include manufacturing and logistics, food industry, circular economy, agriculture sector, and clothing industry with 8, 6, 5, 4, and 3 papers, respectively.

We agreed to create Tables 3.1, 3.2, 3.3 and 3.4 with the author's names and publication year. Listed in the rows, the objective explains the aim of the research works, the method indicates the approach, which is used in the research, the application identifies the area of papers concentrations; citations demonstrated the number of citations related to the paper while the publisher indicated the name of the institute which publishes the paper. These features have been designated based on authors' proficiency in the subject and the applicable investigation. When the relevant works on Industry 4.0 and SSC are combined and studied completely, they show reliable benefits to the readers. These employed benefits explain the master plan for creating the Industry 4.0 and SSC framework in the succeeding sections created on the summary of the content, scope, and outcomes of designated literature. Based on the research in this paper classification, next sections use and recognize the main restrictions and projections in Industry 4.0 and SSC, encapsulate the previous investigation to detect knowledge gaps through offering benefits, drawbacks, and boundaries of specific approaches and present a development dynamic framework as a master plan for upcoming study.

Table 3.5. Top 5 areas of application in the literature of SSC and Industry 4.0.

Number of papers	Area of application	Source
8	Manufacturing and logistics	Baumers et al. (2013); Blümel (2013); Holmström and Partanen (2014); Kiritsis (2016); Prause and Atari (2017); De Carolis et al. (2017); Luthra and Mangla (2018); Forkel et al. (2018)
6	Food industry	Brofman Epelbaum and Martinez (2014); Clear et al. (2013); Pilinkienė et al. (2017); Zhong et al. (2017); Todorovic et al. (2018); Gružauskas et al. (2018)
5	Circular economy (CE)	Jensen and Remmen (2017); Lopes de Sousa Jabbour et al. (2018); Garcia-Muiña et al. (2018); Tseng et al. (2018); Bressanelli et al. (2018)
4	Agriculture sector	Ginige et al. (2016); Kalogianni et al. (2017); Meera et al. (2017); Bucci et al. (2018)
3	Clothing industry	Papahristou and Bilalis (2016); Pal and Sandberg (2017); Papahristou and Bilalis (2017)

3.3. Enabling Technologies and Key Elements of Industry 4.0 for SSC

Several characteristics are not presented in traditional SC while they are required in today's and tomorrow's commercial environment. The conventional SC has a chain of disconnected stages, mostly. Converting a conventional SC into Industry 4.0 and SSC breaks down these walls with the purpose of the chain converts into an integrated system that operates perfectly. Therefore, Industry 4.0 and sustainability allow the succeeding invention of SCs evolve and present mutually productivity and flexibility (Ardito et al. 2019; Büyüközkan and Göçer 2018). Bag et al. (2018) demonstrated the Industry 4.0 enablers of SSC management, which are governmental support; support of research institutes and universities; law and policy about employment; improved IT security and standards; management commitment; focus on human capital; change management; horizontal integration; vertical integration; standardization and reference architecture; and corporate governance and third-party audits. Since Industry 4.0 and sustainability solutions are interrupting conventional SC, there exist several noticeable elements that are practically related to every Industry 4.0 and SSC. These distinct advantages are gathered into some key elements that Industry 4.0 and SSC would like to make. The key elements include speed, flexibility, global connectivity, real-time inventory, intelligent, transparency, cost-effective, scalability, innovative, proactive, and eco-friendly (Büyüközkan and Göçer 2018).

3.4. Challenges, Success Factors, and Research Gaps in Industry 4.0 and SSC

Without considering the companies' size, they need to investigate advancing several kinds of Industry 4.0 and sustainability association competencies since businesses will contest on SCs at worldwide level eventually.

3.4.1. Challenges and Concerns About Executing Industry 4.0 and SSC

Many problems can happen along the SC. Xu (2014) described the chief challenges of building Industry 4.0 and SSC on collecting totally needed data from various suppliers, certifying the correctness of that information, and building up a software design and policy that can use the information to administer and perform the SC. Because the dimension of chain includes inside and outside associates, it will be time consuming and tend to mistake. Furthermore, the current great quantities of stock cannot be capable of fulfilling the demand, and SCs substructure can be inadequate, and the characteristic of products can be difficult to check (Büyüközkan and Göçer 2018). In Table 3.6 we presented 24 recognized challenges for Industry 4.0 and SSC and described each of them briefly.

3.4.2. Success Aspects for Industry 4.0 and SSC

The execution measurement in Industry 4.0 and SSC are especially significant. This measure could be studied by the capability of satisfying requests tills due date, distribution schedule, provider consistency, the budget of chain or postponements, among several others. As stated by a current investigation, over 33% of 2000 respondents have launched employing Industry 4.0 in their SCs, and entirely 72% supposed to have completed so in five years (Schrauf and Berttram 2016). Some motives why Industry 4.0 and SSC implementation has been slowed being the absence of consciousness between the staff and shareholders about digital instruments, and the absence of essential abilities among workers and shareholders (Büyüközkan and Göçer 2018). Consequently, the widespread adoption of Industry 4.0 and SSC will depend on the recognizable aspects of these significant successes so listed in Table 3.7.

Table 3.6. Challenges and issues of implementing Industry 4.0 and SSC

Challenges	Description
Lack of vision and strategy	Industry 4.0 describes an innovative approach to the digital transformation, which requires a clear digital operations vision and mission (Erol et al. 2016).
Lack of planning	Deficiency of proper demand plan and guidelines and tools (Xu 2014; Schrauf and Berttram 2016).
Financial constraints	In Industry 4.0, financial constraints are considered to be a very important challenge in terms of advanced equipment and machines, facilities and sustainable process innovations (Dawson 2014; Theorin et al. 2017; Nicoletti 2018).
Lack of competency in adopting/applying new business models	As it is not necessary that all the new insights of Industry 4.0 will be workable and only some events are interesting out of million events, so revealing these insights are a challenge for data scientists to write suitable algorithms in adopting/applying new business models (Khan et al. 2017; Saucedo-Martínez et al. 2017).
Lack of collaboration and coordination	Deficient collaboration with external associates and deficient input from internal functions (Penthin and Dillman 2015; Xu 2014; EY 2016; Lee et al. 2014; Duarte and Cruz-Machado 2017; Pfohl et al. 2017)
Poor existing data quality	Data quality is one of foremost requirement in making decisions in successful Industry 4.0 adoption and so Inaccurate over-optimistic forecasts for demand, inventory, production, and other data are key challenges (Xu 2014; Carter et al. 2009; Richey et al. 2016; Santos et al. 2017).
Security issues	Security is the prime requirement to transform a factory into a smarter factor and an SC into smarter value chains (Sommer 2015; Wang et al. 2016; Pereira et al. 2017).
Lack of global standards and data sharing protocols	The industries are deficient in standards and protocols, data transfers, adopting sustainability oriented modern information interface technologies and in business networks (Branke et al. 2016).
Lack of information sharing	Companies' reluctance on information sharing (Xu 2014; Nowak et al. 2016).
Lack of infrastructure and internet based networks	High infrastructure, information technology-based facilities, and technologies are crucial in the effective adoption of Industry 4.0 concepts (Leitão et al. 2016; Bedekar 2017; Pfohl et al. 2017).
Low management support and dedication	In order to develop an effective Industry 4.0 concept, management support and dedication to accept the changes are very crucial (Gökalp et al. 2017; Savtschenko et al. 2017; Shamim et al. 2017).
Silver bullet chase:	The belief that everything will be fine (Xu 2014; Hines 2004).
Poor research & development (R&D) on Industry 4.0 adoption	lack of focused research on addressing the various aspects of Industry 4.0 adoption (Schmidt et al. 2015; Hermann et al. 2016).
Lack of knowledge:	Deficiency of SC management training and skills (Xu 2014; Hines 2004).
Lack of digital culture	Industry 4.0 generally of interdisciplinary in nature which requires digitization to connect different elements of a network (Ras et al. 2017; Schuh et al. 2017).
Low understanding of Industry 4.0 implications	There is a very low understanding of Industry 4.0 implications among both the researchers and practitioners (Almada-Lobo 2016; Hofmann and Rüsch 2017).
Agility and Flexibility	Lack of required flexible and agile SC management (Penthin and Dillman 2015; Xu 2014; Hines 2004; Richey et al. 2016; Nabben 2016).
High volatility	Lack of knowledge and skills in dealing with volatility in SC management (Xu 2014; EY 2016; Hines 2004).
Overconfidence in suppliers	Relying on certain suppliers in certain parts of the globe (Xu 2014; Hines 2004).
Profiling and complexity issues	The lack of roadmaps and guides supporting its implementation, as well as its high complexity makes "Industry 4.0" too uncertain for achieving sustainability in SCs (Erol et al. 2016; Ras et al. 2017).

Lack of integration	Deficient view on the integration of digital and non-digital SC management The integration of technology is very essential in effective communication and higher productivity (Zhou et al. 2015; Penthin and Dillman 2015; Xu 2014; EY 2016; Hines 2004).
Unclear economic benefit of digital investments	The lack of clearly defined return on investment could be seen as one of the major challenges to Industry 4.0 initiatives for accomplishing sustainability in the SC (Kiel et al. 2017; Marques et al. 2017).
Lack of governmental support and polices	policy analysts and government bodies have not revealed the roadmap for transforming the traditional business functions into smarter and sustainable processes (BRICS Business Council 2017).
Legal issues	Data privacy and security issues need to be considered in developing data-driven sustainable business models of Industry 4.0 (Schröder 2018; Muller et al. 2017a).

Table 3.7. Success factors for Industry 4.0 and SSC

Success factor	Description
Continuous collaboration:	Capabilities are harmonized within and beyond physical boundaries to increase collaboration between involved actors of the SC (CapGemini 2016; Hines 2004; Accenture 2014).
Real-Time Visibility:	Dynamic, secure and interactive visibility across the entire SC will improve the management of Industry 4.0 and sustainable SC (Cecere 2014; Guarraia 2015; CapGemini 2016; Hines 2004; Accenture 2014).
Integration:	Building the integration of digital and non-digital SCs so that a unified and whole view of inventory across the firm can be achieved (Xu 2014; Raj and Sharma 2014; Schmidt et al. 2015).
Alignment of suppliers:	Aligning the interest of all the firms in the SC with your own to create incentives for better performance and developing trust (alignment) (Xu 2014; Raj and Sharma 2014; Schmidt et al. 2015;CapGemini 2016).
Highly evolved operating models:	Product and service functions can be altered easily to meet customers' changing demands (Raj and Sharma 2014; Hanifan et al. 2014;Accenture 2014).
Shared information:	Industry 4.0 and sustainable SC allows easier information sharing on sales forecast and production data (Xu 2014; Raj and Sharma 2014;Cecere 2014; Schmidt et al. 2015; CapGemini 2016; Hines 2004).
Automated execution:	Seamless human-machine interactions increase operational efficiency (Raab and Griffin-Cryan 2011;Raj and Sharma 2014; Schmidt et al. 2015; Rakowski 2015;CapGemini 2016; GTnexus 2016; Accenture 2014).
Adopting advanced analytics and analytics tools:	Advanced data analysis improves decision making. Gaining better understanding and forecasting of the demand and solve previously unsolvable and even unknown problems along the SC. (e.g., BD and Data Analytics, etc.) (Xu 2014; Raj and Sharma 2014; Hanifan et al. 2014;Accenture 2014).
Maximum efficiency:	Seamless integration of people, processes, and technology (Raj and Sharma 2014; Rakowski 2015).
Enhanced and accelerated innovation:	Digital SCs inspire and abet innovations in designs, operations and customer relationships (Xu 2014; Raj and Sharma 2014;Cecere 2014; Schmidt et al. 2015; Accenture 2014).
Personalized experiences, Customer-centric:	Channel-centric supply networks support customized products and services (Penthin and Dillman 2015;Xu 2014; Raj and Sharma 2014; Schmidt et al. 2015; Hanifan et al. 2014; Accenture 2014).

Organizational flexibility:	Digital plug-and-play capabilities make it easier to configure and re-configure (Raab and Griffin-Cryan 2011;Raj and Sharma 2014;Cecere 2014).
Proactive prevention:	Decision support systems driven by predictive analytics can strengthen adaptability and reliability (Xu 2014; Raj and Sharma 2014; Hanifan et al. 2014;Accenture 2014).
Enhanced responsiveness:	Better information and sophisticated analytics can help accelerate responses to competitors' moves, technology shifts, and changing demand and supply signals (Xu 2014; Raj and Sharma 2014;Cecere 2014; Schmidt et al. 2015; CapGemini 2016; Hanifan et al. 2014; Accenture 2014).
Last mile postponement:	Swiftly repurposing organizational assets assists in ensuring the supplies are aligned with evolving demands (Xu 2014; Raj and Sharma 2014; Hanifan et al. 2014;Accenture 2014).

3.4.3. Research Gaps in Industry 4.0 and SSC

One of the key goals of our investigations is to present a review of the literature of Industry 4.0 and SSC. The literature reviews also presented that few papers were really directed on Industry 4.0 and SSC simultaneously (see Tables 3.1, 3.2, 3.3 and 3.4 and Appendix); however, most of them were directed on empowering of its concentration on SCs. Our study displayed that since there exists a steady growth of research issued on the subject as 2010 for example, from five articles printed in 2010 to 26 articles in 2018, the strong mainstream of papers is still "research papers" (see Fig. 3.2). Hence, more investigation on Industry 4.0 and SSC is required to be done by industries and organizations.

More extensively, research should emphasis on the development frameworks to convert, employ, and accept Industry 4.0 and sustainability in the context of SCs. In spite of the current attention in the Industry 4.0 and SSC subject because of its vast possibilities, the studies that report this topic advantages and contests are in their initial phases. There exist some study gaps in the present sources about Industry 4.0 and SSC that can be condensed as follows:

- Lack of research on implementing Industry 4.0 and sustainability in different industries. As mentioned before, we recognized 55 areas of application, but the number of papers related to each of them is only one. It means there is a vast context for researchers to investigate Industry 4.0 and sustainability in different sectors.
- Deficiency of development frameworks that offer advice for Industry 4.0 and SSC implementation in a perspective with roadmaps and obvious plans. This issue may help in directing executives about what phases and which place in SCs leaders can use Industry 4.0 and SSC, assumed that SCs may be at various stages of the Industry 4.0 and SSC employment. Moreover, development frameworks may offer support in shifting the administration preparations in the SCs.
- Deficiency of technologies and instruments that deal with SCs challenges in the context of Industry 4.0 and sustainability because this context is dissimilar from that of a usual SC. Decisions in an Industry 4.0 and SSC circumstances need novel technologies and tools. Industry 4.0 and SSC will change many processes such as maintenance, quality control, inventory control, planning for manufacture, and purchasing.
- There are many obstacles for the execution of Industry 4.0 and SSC from mutually managerial and technological outlooks. There's rather a substantial transformation occurring in the world. Businesses are at the edge of a contest to change their SCs to Industry 4.0 and sustainable context (CapGemini et al. 2016). Consequently, Industry 4.0 and SSC problems and concerns presented in Subdivision 4.1 require to be answered through the support of Industry 4.0 and SSC success elements resulting from existing literature. There exist not considerable research papers on in what way to deal successfully with these.

In the next section, we will employ all the understanding and information collected from the investigated literature to set up an advanced different framework.

Fig. 3.7. A dynamic framework for the development of Sustainable supply chain 4.0.

3.5. Developing Industry 4.0 and SSC: A Dynamic Framework

Effective SCs work with a well-defined foresight, benefiting frameworks and master plan that describe the path advancing. The present collected works are condensed into four main phases and their sub-objectives. Figure 3.7 displays the dynamic framework in a graphical arrangement created on analysis of the related research works.

The dynamic of this framework is related to Deming's PDCA (plan-do-check-act) process which is a cyclic four-step model for continuous improvement (CI) in commercial procedure management. It means that the PDCA's cycle should be applied in all four main stages as well as their sub-goals and interaction among them.

Therefore, this framework evolves and improves over time via performing corrective actions for eliminating causes of non-conformities. With regard to this dynamic framework, the term "Sustainable Supply Chain 4.0 (SSC 4.0)" is proposed to show the integration of four separated domains in a real-world environment. Actually, SSC 4.0 gradually permits SCs to turn into an integral section of decision-making and tactical developing. Organizations can influence and develop SSC 4.0 to harmonize various aspects of their policies and more successfully direct their definite requirements. The fact is that the vision on the SSC 4.0 literature and projected framework for the development of SSC 4.0 brings the problem of how it can be appropriately applied and proved in regular SC. It should be mentioned that every SC will have a slightly dissimilar set of SSC 4.0 development objectives with diverse main concern. Along with reconsidering and reforming whole SCs, the crucial required assessment objectives for SCs regularly map the fields of Industry 4.0, technology implementation, sustainability, and SC management, which are key phases for administrative arrangement.

By applying this dynamic framework, most of the SC executives will be acquainted with the basic SSC 4.0 methodologies, evaluating the SCs' existing Industry 4.0 and sustainability state, founding a foresight for technology implementation, and expanding a revolution plan for SC management in the novel atmosphere. Explanation of these subjects, their decomposition, and creation of their arrangement along with the PDCA cycle in all stages and interactions are the core of SSC 4.0 employments in usual SC. The disintegrated framework for progressing SSC 4.0 is presented in Tables 3.8 and 3.9.

Table 3.8. Decomposed framework for SSC 4.0

Sustainability	Supply chain	Technology implementation	Industry 4.0
Economic (Pisching et al., 2015a, 2015b) Environmental (Badurdeen et al. 2009) Social (Wittstruck and Teuteberg 2011)	Process (Counsil 2004; Turhan et al. 2011) Integration (Sahin and Robinson 2002, 2005; Bagchi et al. 2005; Alfalla-Luque et al. 2013; Lee 2000) Responsive (Banchuen et al. 2017) Automation (Barratt 2016; Viswanadham 2002) Reconfiguration (Buyukozkan and Gocer 2018) Transpiration and logistics (Speranza 2018) Analytics (Schmidt et al. 2015b; Sahay and Ranjan 2008) Information systems (Agus and Ahmad 2017) Collaboration (Cao and Zhang 2011)	Technology enablers (Ibem and Laryea 2014) Formation of technology infrastructure (Najmi et al. 2016; Klievink 2015) Human and technology relationship (Oyekan et al. 2017) Project management (Yee and Oh 2013)	Virtualization (MacDougall 2014) Interoperability (Saldivar et al. 2015) Decentralization (Gilchrist 2016) Real-time Capability (Vogel-Heuser and Hess 2016) Service orientation (Sanders et al. 2017) Modularity (Peres et al. 2017)

Table 3.9. Decomposed sustainability for SSC 4.0

Sustainability Dimensions	Sustainability Criteria
Economic	Logistics cost; Delivery time; Transport delay; Inventory reduction; Loss/damage; Frequency of service; Forecast accuracy; Reliability; Flexibility; Transport volumes; Applications (Anderson 2007; Fahimnia et al. 2017; Genovese et al. 2017; Sauer and Seuring 2017; Zeng et al. 2017; Monnet and Le Net 2011; Dougados et al. 2013; Gebler et al. 2014; Schrauf and Berttram 2016)
Environmental	Resource efficiency; Process energy; Process emissions; Waste; Pollutions; Land use impact (Nowak 2016; Coyle et al. 2015; Dam and Petkova 2014; Zhu et al. 2011; Gebler et al. 2014; Monnet and Le Net 2011)

Social	Development benefits; Impacts; Health; Safety; Labor patterns; Acceptance (Krause, et al. 2009; Mani, et al. 2016; Kogg and Mont 2012; Gebler et al. 2014; Monnet and Le Net 2011; Schrauf and Berttram 2016)

3.6. Conclusions, Limitations, and Further Research Trends

This review investigates the transformation of SCs to a sustainable supply chain 4.0 (SSC 4.0), an issue of vast interest mutually for specialists and academics. It is absorbing and prepared in a reliable arrangement, so that to show the key suggestions, and created on a method for the progress of an SSC 4.0. To the best of author's knowledge, there is only one paper that considered a literature review for Industry 4.0 and supply chain sustainability. In short, the highlights of the differences of this book chapter with the literature review by Bag et al. (2018) are as follows:

- Adynamic framework is proposed for sustainability and Industry 4.0 in the supply chain (SC) management.
- The term "Sustainable Supply Chain 4.0" (SSC 4.0) is proposed.
- A summary of the documents such as research articles, conference papers, books, and book chapters from 2010 to 2018 is investigated.
- Use different major online databases to get a vast insight into the issues.
- All areas of application in the literature for sustainability and Industry 4.0 in the supply chain (SC) management is recognized.
- Challenges, success factors, and research gaps are determined.

The outcomes of this survey target to response the inquiries for example, what the recent position of SSC 4.0 is in the theoretical, and engineering investigations, along with what the SSC 4.0 future developments seem, and how the present importance of Industry 4.0 and sustainability can be integrated into SC or logistics, and so on. With the intention of illustrating the advancement of inside the SSC 4.0 issues, a review of the research works is offered, learning mismatches in the specified investigation issue are recognized and the features of the previous study are established. Together with this broad analysis of upcoming developments on SSC 4.0, a dynamic framework for SSC 4.0 is settled consistently with the benefits, drawbacks, and restrictions of current SSC 4.0 literature. It is determined to meet the mismatches of former investigations concerning the creation of a comprehensive abstract or academic framework. The recommended dynamic framework goals are at recognizing the characteristics, factors, and technology enablers, success aspects, and disputes for advancing an SSC 4.0. Therefore, the current study and dynamic framework can make available visions to mutually academicians and practitioners in their function of SSC 4.0.

3.6.1. Limitations

With regard to the above-mentioned issues, this review has some restrictions. The following topics summarize these possible restrictions:

- Classified papers in this review of literature are grounded mostly on results from academic journals (consider Fig. 3.2). Adding more industrial reports in the forthcoming can improve this analysis's outcomes.
- The study results are constructed on the exploration of the point out databases by running the entered keywords. As exploration is vastly responsive to these keywords, reviews which take a little diverse enters may be neglected.

- The fact is that in this study a systematic literature review procedure has been employed in which every database is independently explored, and the gathered papers are picked just prior to the examination phases. Another method can be used for organizing these papers obtained in the database.
- We considered a period of previous eight years (2010–2018). We believe these associated research works are friendly on approaches for SSC 4.0. Although the results are not full, we think that they are wide-ranging as they embrace several extremely graded scholarly journals.
- The demonstrated SSC 4.0 dynamic framework aims at employing the integration of Industry 4.0, along with sustainability, technology implementation, and SC management which evolve over time. We have not involved in the extra disintegration of the SSC 4.0 model because it is away from our study.

3.6.2. Future Research Topics

With regards to the above-mentioned restrictions, the succeeding upcoming investigation fashions on SSC 4.0 are constructed on a detailed review of literature along with the previous operational proficiency of writers. Additional examination of these recommendations can produce new awareness and strong concepts in the subject. Hence, the succeeding topics are presented:

- This review proposes a supplementary investigation into manufacturing real-case purposes for the offered SSC 4.0 dynamic framework, demonstrated in Fig. 3.7.
- Businesses from various engineering circumstances are affected by their particular approaches for SSC 4.0, subject to their particular reason of utilizing new Industry 4.0 technologies. Consequently, significant fashions for upcomingSSC4.0 require a clear plan for each to enhance the revolution of its SSC 4.0 tasks. The given category can, consequently, be supplementarily improved to enlighten mutually theoretically with experts' knowledge by creation of sub-frameworks for every business.
- Industry 4.0 and sustainability will change the approach of SCs. For the purpose of appropriate application and confirmation of the development framework, the offered steps should be understood and evaluated in typical SC.
- Although the benefits and restrictions of SSC 4.0 have been examined at a theoretical level, more developments are needed yet in some parts of SSC 4.0 so that a strong, consistent, and flexible solution is obtained for useful execution of SSC4.0 into engineering real-case functions.
- Additionally, the advantages and disputes of SSC 4.0 can be investigated for the superior recognition of the possibility and success of the recommended dynamic framework.
- To summarize, the equipment and elements of SSC 4.0 can be joined to further the current SC-associated investigations in equally scholar journals and engineering reports. SSC 4.0 is vastly far from implementing its greatest ability, and as stated in this study, there exist many fields (55 topics are recognized by this study) that need urgent consideration.

Paper Appendix-Chapter 3

See Tables 3.10, 3.11 and 3.12.

Table 3.10. The areas of application and Nomenclature

The areas of application	Nomenclature
3D technologies	3DT
Agriculture sector	AG
Automotive	AUTO
Biologicalisation	BIOL
Blockchain technology	BLOC
Business model	BM
Circular economy (CE)	CE
Clothing industry	CLI
Construction industry	Con
Digital assorting system (DAS)	DAS
Digital business landscape	DBL
Digital China Company's SC integration system	DCSC
Digital enterprises	Den
Digital mine	Dmi
Digital-training method	DTr
Digitization	DIGI
Direct digital manufacturing (DDM)	DDM
Distributed manufacturing	DisMa
E-CRM strategy	ECER
Electronic industry	EleI
E-procurement technologies	Eproc
E-Residency	Eres
FoFdation Smart Machine Controller (SMC)	SMC
Food industry	FoI
Forest-based supply chains	ForSC
Global 3PLs operating	3PLs
Global economy	GloEco
Green supply chain	GSC
Information communication technology (ICT)	ICT
Innovation Union	InnU
Intelligent Autonomous Vehicles (IAVs)	IAVs
Intelligent Transport Systems (ITS)	ITS
Manufacturing and logistics	ManLog
Networked information-based technologies	NetInfoTech
Newspaper Industry	NewsIn

Paper manufacturing	PapMan
Pharmaceutical supply chain (PSC)	PSC
Physical Internet	PhyInt
Policy-making	PoliMak
Rail-road intermodal transport network	RailROAD
Reconfigurable Manufacturing Systems (RMS)	RMS
Record labels and retail outlets	RecLab
Reverse logistics	RevLog
SemProM project	SemProM
Sendai Framework for Disaster Risk Reduction (SFDRR)	SFDRR
Simulation optimization	SimOpt
Small-scale Intelligent Manufacturing System (SIMS)	SIMS
Smart City	SmaCit
SME networking	SME
Supply chain sustainability	SSC
Thermoplastic composite structures	TherPlaCOM
Trade promotion	TradPro
Transport and logistics	TransLog
Virtual digital retail ecosystem	VDREco
Waste electrical and electronic equipment (WEEE)	WEEE

Table 3.11. Literature Review of sustainable SC and Industry 4.0 (Research papers).

Year	Authors	Objective	Method	Area of application
2010	Dzopalic et al.	Introducing E-CRM strategy	Case study	E-CRM strategy
2011	Norris	Introducing a new program called the Newspaper Industry Environmental Vision which is gathering a critical mass of newspaper publishers and printers calling for increased efforts in industry best practices and sustainability.	Modelling	Newspaper Industry
2011	Hajdul and Cudzilo	Presenting how the Common Framework supports interoperability between commercial actors and communication to authorities and transportation network responsible.	Case study	Transport and logistics
2012	Agarwal et al.	Studying the consumer return behaviour of end of life goods at different incentive levels and make an attempt to incorporate the latest research practices.	Modelling	Waste electrical and electronic equipment (WEEE)
2012	Lin et al.	Creating digital mine and key technologies in China.	Modelling	Digital mine
2012	Davis et al.	Introducing Smart manufacturing, manufacturing intelligence and demand-dynamic performance.	Modelling	Networked information-based technologies

2013	Hentza et al.	Describing the on-going work with a specific focus on the definition and implementation of the FoFdation Smart Machine Controller (SMC) in an adaptable architecture that satisfies both commercial and open source CNC controllers.	Modelling	FoFdation Smart Machine Controller (SMC)
2013	Zhu et al.	Investigation of BIM digital technology in the construction industry.	Review	Construction industry
2013	Blümel	Studies means by which digital engineering and virtual and augmented reality technologies can support the creation of sustainable smart manufacturing and smart logistics processes as well as on-the-job training and qualification and knowledge transfer.	Modelling	Manufacturing and logistics
2013	Clear et al.	Brings together participants from a diverse range of disciplines to develop an understanding of existing food consumption practices, and how this domain can profit from novel Ubicomp technology and interaction designs.	Modelling	Food industry
2013	Baumers et al.	Studying whether the adoption of additive manufacturing (AM) technology can be used to reach transparency in terms of energy and financial inputs to manufacturing operations.	Modelling	Manufacturing and logistics
2014	Gebler et al.	Representing the first comprehensive assessment of 3DP from a global sustainability perspective.	Modelling	3D technologies
2014	Holmström and Partanen	Exploring the forms that combinations of digital manufacturing, logistics and equipment use are likely to take and how these novel combinations may affect the relationship among logistics service providers (LSPs), users and manufacturers of equipment.	Modelling	Manufacturing and logistics
2014	Brofman Epelbaum and Martinez	Offering a theoretical framework grounded on the Resource-Based View (RBV) of the firm to determine the strategic impacts of the technological evolution of food traceability systems.	Case study	Food industry
2015	Yue et al.	Defining the development and character of ICPS and offering a service-oriented ICPS model.	Modelling	Information communication technology (ICT)
2015b	Chen, R.-Y.	Simulating complex system by connected physical and digital objects with relationships while enhancing decision-making performance efficiency for green inventory management.	Modelling	Green supply chain
2015	Prause	Responding to the research question of how new and sustainable business models and structures for Industry 4.0 might appear and in which direction existing traditional business concepts have to be developed to deploy a strong business impact of Industry 4.0.	Modelling	E-Residency
2016	Papahristou and Bilalis	Analyzing the challenges, the threats and the opportunities across the SC partners emerging to reduce the environmental footprint.	Modelling	Clothing industry
2016	Ranzo et al.	Studying new mobility and manufacturing concepts, carried out in the framework of a research project funded by the Regional	report	Automotive supply chain

		Government of Campania for innovative development of the automotive SC.		
2016	Lom et al.	Suggesting the conjunction of the Smart City Initiative and the concept of Industry 4.0.	Modelling	Smart City
2017	Lin et al.	Using a descriptive analysis with descriptive statistics under the innovation policy framework proposed by Rothwell and Zegveld. Moreover informing a comparative policy analysis across China and Taiwan.	Case study	Policy-making
2017	De Carolis et al.	Illustrating a "tool" for building a maturity assessment method to measure the digital readiness of manufacturing firms.	Modelling	Manufacturing and logistics
2017	Man and Strandhagen	Considering potential sustainable business scenarios, and proposes an agenda for research into how Industry 4.0 can be used to create sustainable business models.	Modelling	Business model
2017	Palm	Studying recent trends of vinyl traffic and critique a prominent feature of contemporary vinyl culture: Record Store Day.	Review	Record labels and retail outlets
2017	Rauch et al.	Considering the actual state of the art in distributed manufacturing.	Review	Distributed manufacturing
2017	Jensen and Remmen	Investigating how different 'product stewardship' and 'end-of-life' strategies can support the circular economy and what the challenges and benefits are from an original equipment manufacturer perspective.	Modelling	Circular economy (CE)
2017	Lee et al.	Explaining to what extent the business sectors involved in and how to safeguard the cross-border trade and investments with safer and smarter regional strategies in the digital age with large-scale disasters.	Modelling	Sendai Framework for Disaster Risk Reduction (SFDRR)
2017	Zhong et al.	Studying food SC management (FSCM) in terms of systems and implementations.	Modelling	Food industry
2017	Paul and Zhou	Studying an empirical case of a leading paper manufacturing company in central Java, Indonesia, in their way of building their maintainable innovation capability in their SC by applying a combination of various existing models.	Case study	Paper manufacturing
2017	Strandhagen et al.	Studying the challenges of Industry 4.0, current trends, and offering a model to understand and relate the different elements of business operations.	Review	Business model
2017	Prause and Atari	Exploring the relationship between networking, organizational development, structural frame conditions and sustainability in the context of Industry 4.0.	Case study	Manufacturing and logistics
2017	Papahristou and Bilalis	Considering the relationship between Corporate Social Responsibility (CSR) and Collective Actions on Sustainability and the environmental impact of the new model of fast and accelerating fashion.	Modelling	Clothing industry
2018	Tombido et al.	Reviewing the literature on the entry and use of third parties in reverse logistics with the objective of providing researchers with future research directions for this fast-emerging topic.	Review	Reverse logistics

2018	Byrne et al.	Studying the meaning and implications of "Biologicalisation" from the perspective of the design, function and operation of products, manufacturing processes, manufacturing systems, SCs and organizations.	Modelling	Biologicalisation
2018	Saberi et al.	Studying Blockchain technology and smart contracts with potential application to SC management.	Modelling	Blockchain technology
2018	Scholz et al.	Considering digital technologies in forest-based SCs and summarizing the state-of-the-art digital technologies for the real-time data collection on forests, product flows, and forest operations, along with planning systems and other decision support systems in use by SC actors.	Review	Forest-based supply chains
2018	Banks et al.	Explaining enhancing high-rise residential construction through design for manufacture and assembly.	Case study	Construction industry
2018	Luthra and Mangla	Recognizing key challenges to Industry 4.0 initiatives and key challenges for SC sustainability in emerging economies by taking Indian manufacturing industry perspective.	Review	Manufacturing and logistics
2018	Nascimento et al.	Studying how rising technologies from Industry 4.0 can be integrated with a circular economy (CE) practice to establish a business model that reuses and recycles wasted material such as scrap metal or e-waste.	Modelling	Circular economy (CE)
2018	Bag et al.	Recognizing the Industry 4.0 enablers of SC sustainability and further attempt to propose a research framework to bridge the theoretical gaps.	Review	Supply chain sustainability
2018	Lopes de Sousa Jabbour et al.	Offering a pioneering roadmap to improve the application of CE principles in organizations by means of Industry 4.0 approaches.	Case study	Circular economy (CE)
2018	Bechtsis et al.	Providing a framework that obtains the main software architecture elements for developing highly customized simulation tools that support the effective integration of Intelligent Autonomous Vehicles (IAVs) in sustainable supply networks, as an emerging field in the operations management agenda.	Modelling	Intelligent Autonomous Vehicles (IAVs)
2018	Sendlhofer and Lernborg	Studying how workers are trained on their labour rights with a digital-training method.	Case study	Digital-training method
2018	Gružauskas et al.	Examining the limited possibilities to reach cost-effective performance and sustainability.	Review	Food industry
2018	Sun et al.	Offering an agent-based simulation that models the micro-level protocols of mobile recourse units and their interaction with the physical infrastructure in a rail-road intermodal transport network.	Modelling	Rail-road intermodal transport network
2018	Ding	Recognizing the potential sustainability barriers of PSC and examining how Industry 4.0 can be applied in the sustainable PSC paradigms.	Review	Pharmaceutical supply chain (PSC)
2018	Bucci et al.	Presenting an overview of worldwide development and status of precision agriculture, starting from 2000 until to date.	Review	Agriculture sector

2018	Forkel et al.	Investigating Smart Interoperable Logistics and Additive Manufacturing - Modern Technologies for Digital Transformation and Industry 4.0	Modelling	Manufacturing and logistics
2018	Todorovic et al.	studying how the SFSC could be designed from the aspects of innovative logistics modes and contemporary information and communication technologies, with the final aim to outline and evaluate different food distribution scenarios towards greater sustainability.	Modelling	Food industry
2018	Holmström et al.	Investigating how current and future Direct digital manufacturing (DDM)-based operational practices can be used to advance products and processes.	Modelling	Direct digital manufacturing (DDM)
2018	Wu et al.	Studying how to provide trade promotions in a sustainable manner when consumer demand is disrupted.	Modelling	Trade promotion
2018	Garcia-Muiña et al.	Exploring the phases of the transition from a linear to a circular economy and suggesting a procedure for the principles of sustainability (environmental, economic and social) in a manufacturing environment, through the design of a new Circular Business Model (CBM).	Modelling	Circular economy (CE)
2018	Bressanelli et al.	Recognizing the main challenges that companies have to face when they want to redesign their SC according to CE principles, i.e. to implement a circular SC.	Review	Circular economy (CE)
2018	Delina et al.	Suggesting a framework for innovation-driven SC ecosystem based on interoperability between commercial and public innovation procurement organization and research environment. Moreover developing single digital infrastructure for supporting critical issues in requirements analysis, sourcing, negotiation, contract execution and post-contractual phase to build sustainable, motivational and trusted innovation-driven environment.	Modelling	Innovation Union
2018	Dallasega and Sarkis	Examining the nexus of Industry 4.0 and greening SCs with using proximity analysis.	Modelling	Supply chain sustainability

Table 3.12. Literature Review of sustainable SC and Industry 4.0 (Conference papers).

Year	Authors	Objective	Method	Area of application
2010	Pöltner and Grechenig	Offering a concept for the establishment of a future virtual digital retail ecosystem	Modelling	Virtual digital retail ecosystem
2010	Price et al.	Proposing a digital framework for the creation and management of performance parameters related to the lifecycle performance of thermoplastic composite structures.	Modelling	Thermoplastic composite structures
2010	Kang and Diao	Analyzes the route choice of information technology(IT) which enterprises can obtain long-term competitive advantages.	Modelling	Digital China Company's Supply Chain integration system
2012	Ji and Niu	Studying variety and high-frequency necessities of modern cold chain logistics, and application of digital assorting system (DAS) in cold chain logistics warehousing system To meet the JIT.	Modelling	Digital assorting system (DAS)
2013	Bjorn et al.	Explaining how a general operating model of re-use of electrical and electronic equipment (EEE), and specifically for PCs in developing countries, deal with the challenges and opportunities of increasing e-waste awareness.	Case study	Electronic industry
2015	Tzoulis et al.	Combining data on timber trade in Greece and also studying how the economic crisis has affected the forest, its products and how it has affected trade (imports and exports).	Case study	Forest-based supply chains
2016	Ginige et al.	Studying a notion of context-specific actionable information which allows the user to act with the least amount of further processing.	Case study	Agriculture sector
2017	Kalogianni et al.	Studying an efficient Monitoring and Control software Tool (MCT) for assessing the operation data of an olive oil production facility.	Modelling	Agriculture sector
2017	Yu and Solvang	Presenting a new concept: Small-scale Intelligent Manufacturing System (SIMS), and the comparison with previous concepts and the benefits of SIMS are discussed in this paper.	Modelling	Small-scale Intelligent Manufacturing System (SIMS)
2017	Pilinkienė et al.	Investigating a case study of the European Union food industry by modelling different logistic network scenarios, and implemented a competitiveness strategy based on the Industry 4.0 concept and lean philosophy.	Case study	Food industry
2017	Tan et al.	Considering how organizations can investigate and implement techniques for their modern enterprise with a focus on how advanced big data tools can be applied to Quality Analytics for monitoring and improving quality in the electronic industry.	Modelling	Electronic industry
2017	Crowley et al.	Literature reviewing and discussing core learnings in relation to impacts on sourcing and supplier management in a digital business landscape.	Review	Digital business landscape
2017	Pal and Sandberg	Studying the inter-organizational value creation, in apparel SC context, through circularity and	Modelling	Clothing industry

2018	Alrabghi	digitalization for sustainability, by gathering evidence from vivid research experiences. Investigating the key elements of simulation optimization frameworks that will facilitate the transformation to industry 4.	Review	Simulation optimization

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Industry 4.0 and demand forecasting of the energy supply chain: A literature review

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A R T I C L E I N F O

Keywords:
Demand forecasting
Demand of energy
Supply Chain (SC)
Intelligent methods
Industry 4.0

A B S T R A C T

The number of publications in demand forecasting of the energy supply chain augmented meaningfully due to the 2008 global financial crisis and its consequence on the global economy, mainly in energy supply chains. In spite of the fact that Industry 4.0 emerged during this period, its solutions and their impacts on energy demand forecasting are not covered by current reviews in the literature. This paper presents a comprehensive and up-to-date review of publications related to forecasting approaches of energy demand in the last two decades between 2000 and 2020 with an emphasis on Industry 4.0 influences and the state-of-the-art progress on this topic. A total of 267 publications are chosen and about 73 distinctive approaches of energy demand forecasting are discovered. Accordingly, among these approaches, there are eight methods with the most citations which include 56% of the total articles. Additionally, the forecasting methods are classified into traditional and intelligent methods and the most cited publications related to both are reviewed in detail. Furthermore, the advantages and disadvantages of both traditional and intelligent forecasting methods as well as research limitations and future researches are determined. The results from the literature review indicated that by employing intelligent forecasting methods, the errors and costs were reduced while these methods increase profitability.

1. Introduction

Nowadays, most enterprises are going through digitization, which is known as Industry 4.0 (Roozbeh Nia, Awasthi, & Bhuiyan, 2020). The digital revolution focuses generally on manufacturing, therefore, names such as “Smart Factory” or “Factory of the Future” are used and matched with this concept (Kayikci, 2018). Under such conditions as globalization, rapidly-evolving technology, and progressively demanding customers, corporations in the same supply chain (SC) must collaborate to fulfill customer requirements superior to their competitors (Marchi & Zanoni, 2017). Furthermore, the main influence motivating Industry 4.0 is to guide businesses by applying digital technologies that recognize methods that can assist organizations in creating connections among their operations, systems, manufacturing capabilities, finished goods, and clients. The intention of these technologies is collecting and distributing real-time functioning and marketplace information with stakeholders (Ardito, Petruzzelli, Panniello, & Garavelli, 2019).

The digitization in SCs is based on six features: connectivity, cooperation, integration, adaptiveness, cognitive improvement, and autonomous control (Kayikci, 2018). With the purpose of boosting opportunities, decreasing costs, and gaining competitive advantage, energy corporations are increasingly reconsidering their SCs. The energy division is segregated into various sections, each with their own SC problems and challenges. The common five sub-sectors in the energy SC division are presented in Fig. 1. The energy market today is mutually maturing and unbalanced, distinguished through growing demand and variable supply. However, the greatest challenges come from the scheduling of demand and forecasting precision and with that the configuration of materials and supply with energy demand (DHL 2015).

Supply chain collaborations can potentially enhance energy efficiency, yet most businesses still pay secondary consideration to whether their partners employ energy management systems, including energy forecasting in their commercial process (see Fig. 2). Cooperation between SC partners will improve value to each partner and the SC in the function of a system, while costs can be avoided, risks can be divided, and lead and response time can be diminished in an ever-fluctuating commercial environment (Jansen, 2014; Marchi and Zanoni, 2017). Moreover, the term “energy demand” generally denotes any kind of energy needed to meet individual or sectoral energy requirements (Hasanuzzaman, Islam, Rahim, & Yanping, 2020). Therefore, energy

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CHAPTER 4. PAPER TWO - INDUSTRY 4.0 AND DEMAND FORECASTING OF THE ENERGY SUPPLY CHAIN: A LITERATURE REVIEW

Forewords

After reviewing the research works in "Management of Sustainable Supply Chain and Industry 4.0" in previous Chapter, now in this Chapter, a comprehensive literature review of "Industry 4.0 and demand forecasting of the energy supply chain" are presented. Moreover, in Chapters 5 and 6 (subsection 5.2 and 6.2) a complete review of research works related to exergy analysis and carbon reduction policies are presented.

Abstract

The number of publications in demand forecasting of the energy supply chain augmented meaningfully due to the 2008 global financial crisis and its consequence on the global economy, mainly in energy supply chains. In spite of the fact that Industry 4.0 emerged during this period, its solutions and their impacts on energy demand forecasting are not covered by current reviews in the literature. This paper presents a comprehensive and up-to date review of publications related to forecasting approaches of energy demand in the last two decades between 2000 and 2020 with an emphasis on Industry 4.0 influences and the state-of-the-art progress on this topic. A total of 267 publications are chosen and about 73 distinctive approaches of energy demand forecasting are discovered. Accordingly, among these approaches, there are eight methods with the most citations which include 56% of the total articles. Additionally, the forecasting methods are classified into traditional and intelligent methods and the most cited publications related to both are reviewed in detail. Furthermore, the advantages and disadvantages of both traditional and intelligent forecasting methods as well as research limitations and future research are determined. The results from the literature review indicated that by employing intelligent forecasting methods, the errors and costs were reduced while these methods increase profitability.

Keywords Demand forecasting; Demand of energy; Supply Chain (SC); Intelligent methods; Industry 4.0

4.1. Introduction

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The digitization in SCs is based on six features: connectivity, cooperation, integration, adaptiveness, cognitive improvement, and autonomous control (Kayikci, 2018). With the purpose of boosting opportunities, decreasing costs, and gaining competitive advantage, energy corporations are increasingly reconsidering their SCs. The energy division is segregated into various sections, each with their own SC problems and challenges. The common five sub-sectors in the energy SC division are presented in Fig. 4.1. The energy market today is mutually maturing and unbalanced, distinguished through growing demand and variable supply. However, the greatest challenges come from the scheduling of demand and forecasting precision and with that the configuration of materials and supply with energy demand (DHL 2015).

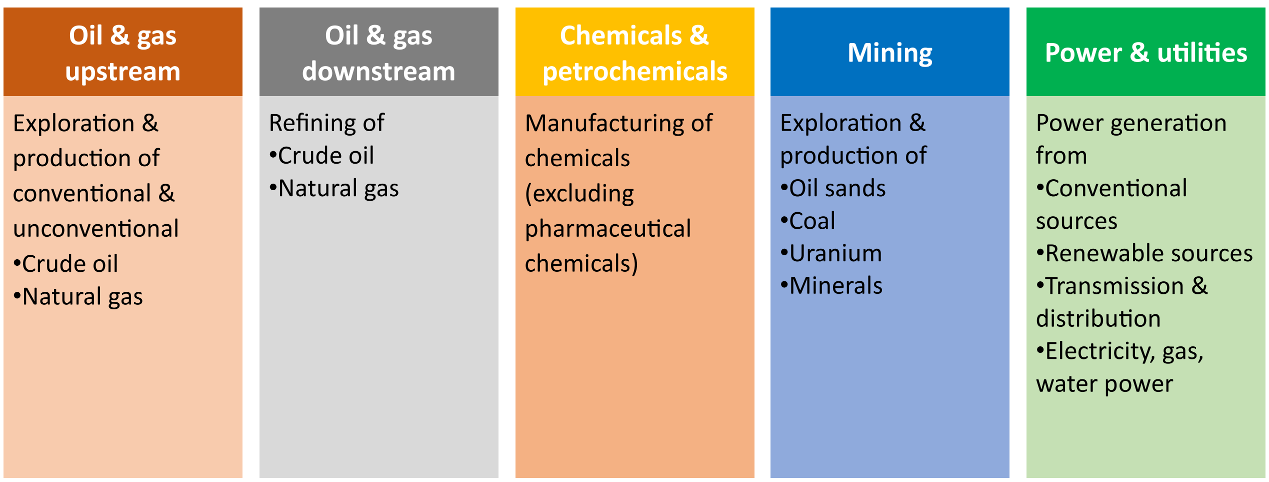

Fig. 4.1 The sub-sectors in Energy SC division

Supply chain collaborations can potentially enhance energy efficiency, yet most businesses still pay secondary consideration to whether their partners employ energy management systems, including energy forecasting in their commercial process (see Fig. 4.2). Cooperation between SC partners will improve value to each partner and the SC in the function of a system, while costs can be avoided, risks can be divided, and lead and response time can be diminished in an ever-fluctuating commercial environment (Jansen, 2014; Marchi and Zanoni, 2017). Moreover, the term “energy demand” generally denotes any kind of energy needed to meet individual or sectoral energy requirements (Hasanuzzaman, Islam, Rahim, & Yanping, 2020). Therefore, energy demand can be grouped into several divisions through end-users. Consistent with the International Energy Agency (IEA, 2017), the energy demand sector categorizations are presented in Fig. 4.3. Note that in Fig. 4.3 other sector forms agriculture and fishing (IEA, 2017).

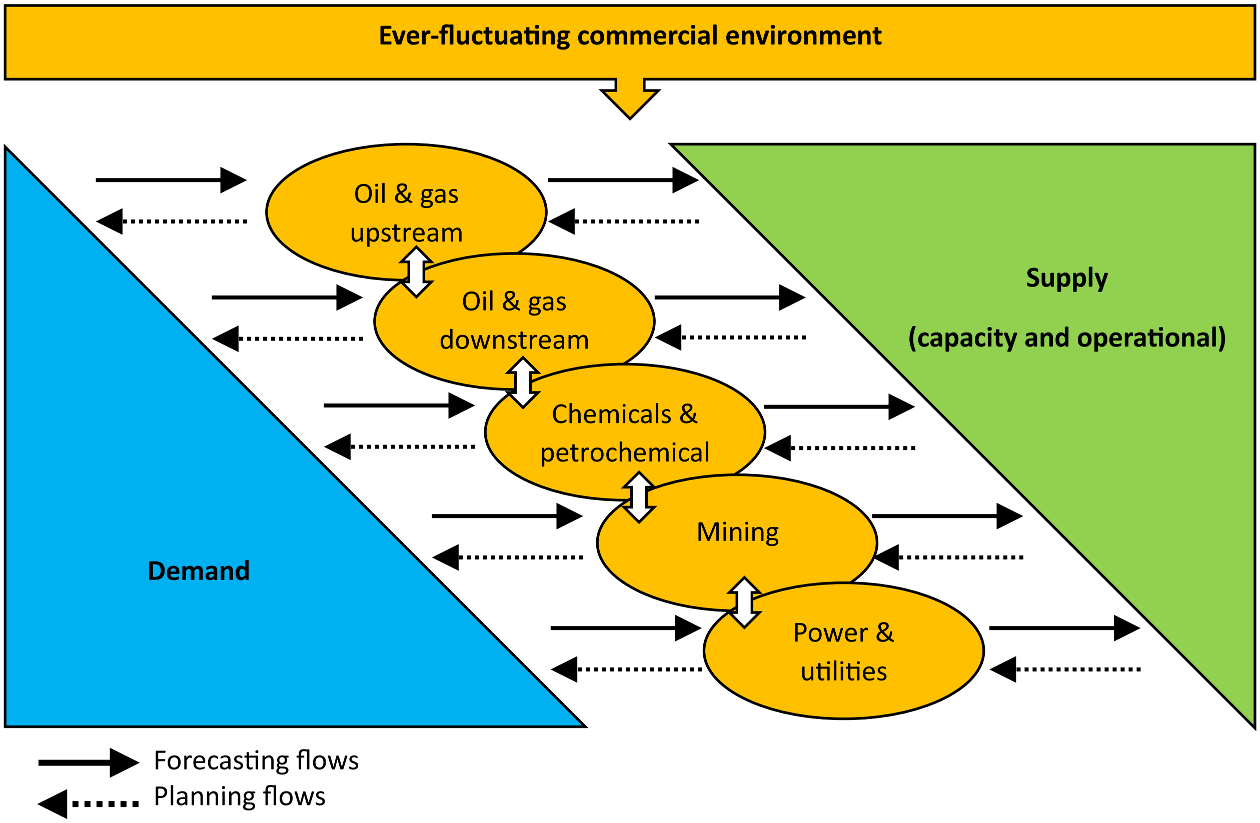

Fig. 4.2 The energy SC, demand and forecasting

Management of energy is critical for economic success and environmental security since energy is connected to many sectors such as industrial manufacture, agricultural production, access to water, education, health, population, life quality, etc., (Suganthi & Samuel, 2012). Besides, industry and governments must concurrently follow these three issues (S´anchez-Dur´an, Luque, & Barbancho, 2019):

- Energy security (consistency of energy infrastructure, and capability of energy suppliers to fulfill present and upcoming demand),
- Energy equity (availability and affordability of energy supply for the population),
- Environmental sustainability (energy productivity and the improvement of energy provided by renewable and other low-carbon sources).

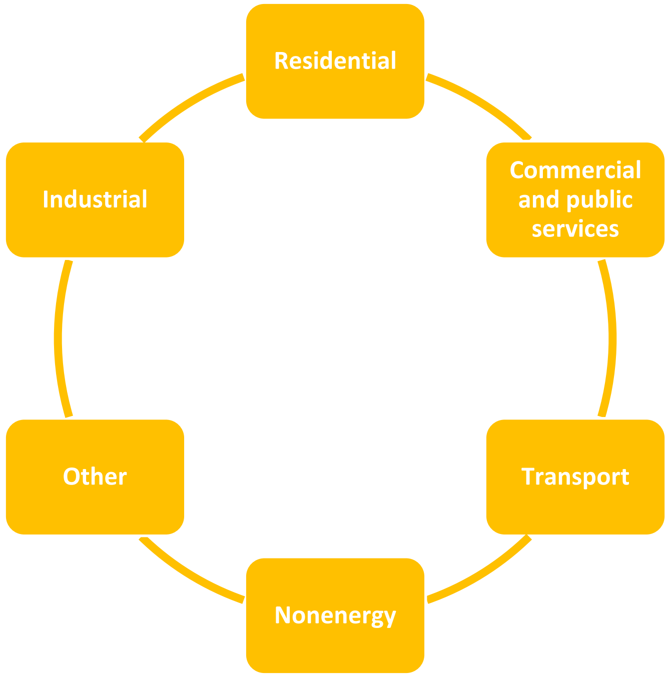

Fig. 4.3 Classifications of energy demand sectors

Unquestionably, excessive consumption of energy has a significant impression and damaging consequence on the environment. Hence, for a country and mainly in developing countries, energy demand is a core concern in developing energy strategies (Pi, Liu, & Qin, 2010). For example, the management of energy in China, including energy supply and demand, has performed a critical role (Liu, 2015), so that the prediction of energy demand has been an increasingly vital subject (Suganthi & Samuel, 2012). Therefore, it is essential to develop effective forecasting methods for energy demand (Hu, 2020). The term "forecasting" is described by the procedure of estimation, prediction, or projection of upcoming activities, events, or occurrences. Consequently, energy demand forecasting is based on the different data and information accessible. In general, demand forecasting is done by estimating past data/information through mathematical models to forecast the trend of forthcoming energy demand (Islam, Che, Hasanuzzaman, & Rahim, 2020).

From the viewpoint of a decision-maker, a well-functioning SC is the support of almost every business. To ensure a close balance between supply and demand, a very precise demand forecasting linked with enhanced replenishment policies is key (McKinsey, 2017). On the other hand, in competitive energy markets, the precise prediction of monthly, quarterly, and yearly energy consumption can deliver an advantage in dialogs and carrying out contracts for medium-term generation, transmission, and distribution (Pelka & Dudek, 2019). Also, a reliable long-term energy demand estimate is essential to recognize the energy demand and present valuable supports for outlining strategic decisions. As a result, selecting proper modeling approaches consistent with features of estimated areas is the first duty for the correct forecasting of energy demand (Chen, Rao, & Liao, 2019).

Despite the fact that recent review articles surveyed energy demand forecasting in a specific branch, such as electricity (Shao, Chao, Yang, & Zhou, 2017), natural gas (Khan, 2015; Melikoglu, 2013), building energy (Ahmad, Chen, Guo, & Wang, 2018), solar power (Ahmed, Sreeram, Mishra, & Arif, 2020), etc. and make a category in the specific fields, few pay attention comprehensively to demand forecasting methods of all energy types in the literature. For example, Suganthi and Samuel (2012) presented a list of the forecasting methods used for energy demand and described each method in detail. After that, Ghalehkhondabi, Ardjmand, Weckman, and Young (2017) studied the ten most-employed energy demand forecasting methods in the last ten years between 2005 and 2015.

To the best of the authors' knowledge, the two above-mentioned articles were only reviewed that considered energy demand forecasting methods. However, they ignored Industry 4.0 solutions in this subject, and the time span they studied was not comprehensive. As a result, to fill the gap in the literature, we provide a comprehensive and updated review of publications related to forecasting methods of energy demand in the last two decades between 2000 and 2020 with focusing on Industry 4.0 influences and the state-of-the-art progress in this subject. Contrasted with the existing reviews on similar subjects, the novelties, and contributions of this review are as follows:

- We focus on Industry 4.0 solutions and the effects of them in energy demand forecasting.
- We categorize energy demand forecasting methods to traditional and intelligent methods and review the most cited publications related to both in detail.
- In terms of time span, we consider a comprehensive review of publications such as research articles, conference papers, books, and book chapters in the last 20 years from 2000 to 2020.
- In terms of energy type, we consider all types of energy.
- We highlight the advantages and disadvantages of both traditional and intelligent forecasting methods as well as research limitations and future researches are determined.

This review is organized in this mode: the next section reviews, categorizes, and presents some analysis of associated publications in the last two decades (2000–2020), along with explaining the methodology supposed in this review. Reviewing the most cited traditional and intelligent methods of energy demand forecasting that is resulting from the current literature as well as related top papers are represented in Sections 4.3 and 4.4, respectively. Lastly, the review's concluding remarks, the restrictions, plus some suggestions for energy demand forecasting in the Industry 4.0 era, are presented in Section 4.5.

4.2. Literature Review

The review of the last two decades' research work is built on arrangement procedure. First, the arrangement exploited in this review is explained, and later, the process of the literature review is described.

4.2.1. Method of reviewing

Related research works are distinguished through a comprehensive online exploration that aims to gather, classify, and synthesize current demand forecasting of energy SC in the Industry

4.0 era. The literature is reviewed for the period 2000–2020 by exploring Thomson Reuter's Web of Science. As a result of the insufficiency of exact keywords explaining the subject, we put a substantial attempt to sort publications by reviewing their titles, abstracts, and texts. We investigate and organize related research works to meet a vision of energy demand forecasting in the Industry 4.0 era. Normally, this step can be achieved by aiming for noticeable journals, books, and conferences. At first, we considered keywords like "demand forecasting" and "energy demand" in the "TOPIC" search field of Thomson Reuter's Web of Science. There were more than 4500 articles that, after investigation, were found not to be related to our objective. We refined our search to the "TITLE" search field and the results were more exact with 208 articles. Since in the literature, the word "Prediction" is used as well, we did a new search with this keyword "demand prediction" and found 87 more articles. After that, we put a considerable attempt to sort all papers by studying their titles, abstracts, texts, and removing unrelated articles. Finally, we considered 267 articles that were within our objective. The general review methodology for demand forecasting of energy SC and Industry 4.0 articles is as follows:

Step 1- Finding the sources (online databases)

Step 2- Searching keywords

Step 3- Developing a taxonomy and analysis based on journal papers, conference papers, books, theses, etc.

Step 4- Identifying research with implications and issues related to demand forecasting, energy SC, Industry 4.0, Features, Component and technologies, Challenges, and advantages.

Step 5- Presenting Survey outcomes: conclusions, limitations, and further research.

4.2.2. Summary of statistical analysis

Although in this study, the literature is reviewed for the period 2000–2020, initially, to understand the bigger picture in demand forecasting of energy SC, we considered the time of 1979–2020. We used the search tool of Thomson Reuters Web of Science with keywords "demand forecasting" and "energy demand" in the "TITLE" search field. We did the same thing with the keyword "demand prediction" as well. We investigated criteria such as the number of publications per year, countries/regions, document types, energy types, applications, and research areas. Based on publication years, ranging from 1979 to 2007, the number of related publications in this area was under five research works per year (see Fig. 4.4). Although from 2008 until 2020, there is a sharp increasing trend, it could be shown that after the global monetary crisis in 2008, researchers and industries understand better the importance of energy demand prediction due to cost-saving issues.

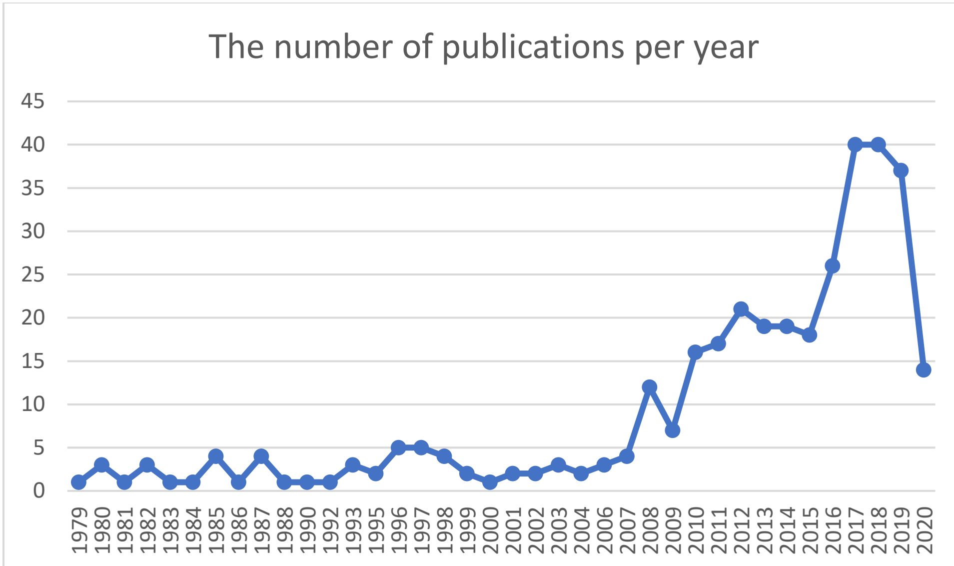

Fig. 4.4 The number of publications from 1979 to 2020

Considering Fig. 4.5, the top five research areas from 1979 to 2020 are Energy fuels (23%), Engineering (22%), Computer science (11%), Environmental sciences ecology (8%), and Business economics (7%), respectively. Given document types, more than half of the publications are Articles (60%), following with Proceedings papers (37%) and Reviews (1%), respectively (see Fig. 4.6). In the role of countries/regions as Fig. 4.7, the top three countries with the most publications in energy demand forecasting are China (27%), USA (11%), and Iran (6%), respectively. Generally, China & USA are the two biggest energy consumers, while Iran is one of the biggest energy producers (Oil and Gas) in the world. It could be recognized that since both suppliers and buyers of energy in the world are concerned about forecasting and the outlook of energy markets, local universities and research institutions focused on this topic. By investigating the energy types of each article from 2000 to 2020, more than half of them (59%) studied demand forecasting of Electricity (see Fig. 4.8). In the second and third ranks, Coal and Oil are with 17% and 10%, respectively. Once fossil fuels are gone, they cannot be replaced, so decision-makers are now keen to use renewable sources of energy. Renewable energy is an interesting issue, but only 3% of publications considered it. It is expected that this percentage will increase in the next decade. Considering the application of research, the authors found 36 different areas. About (34%) of total publications studied National energy demand (see Fig. 4.9). This is followed by forecasting energy demand of Building and Regions (City/province) with 15% and 9%, respectively. Finally, according to the type of methodology used in publications from 2000 to 2020, top three methods are Neural network, Metaheuristic algorithms and Grey model, respectively (see Fig. 4.10).

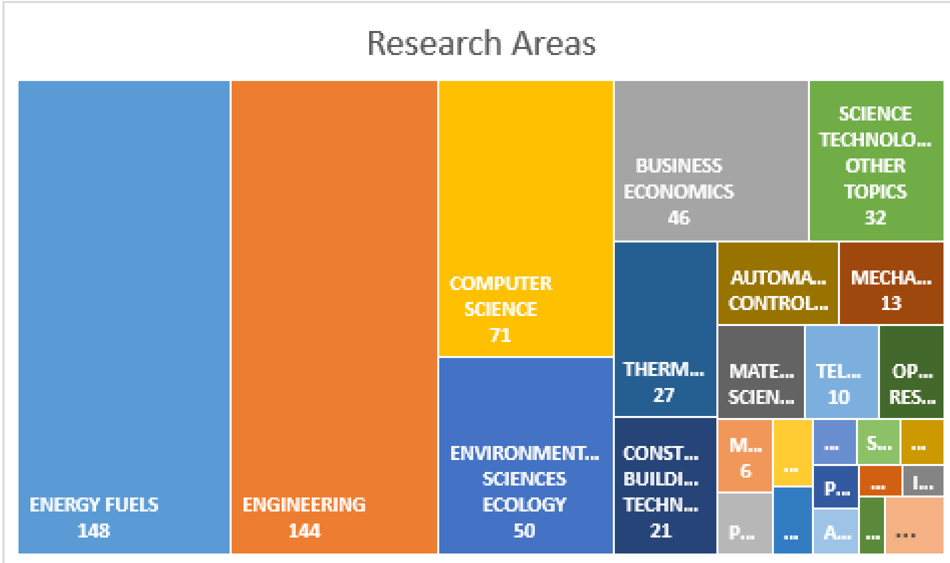

Fig. 4.5 Research areas and their publication's number from 1979 to 2020

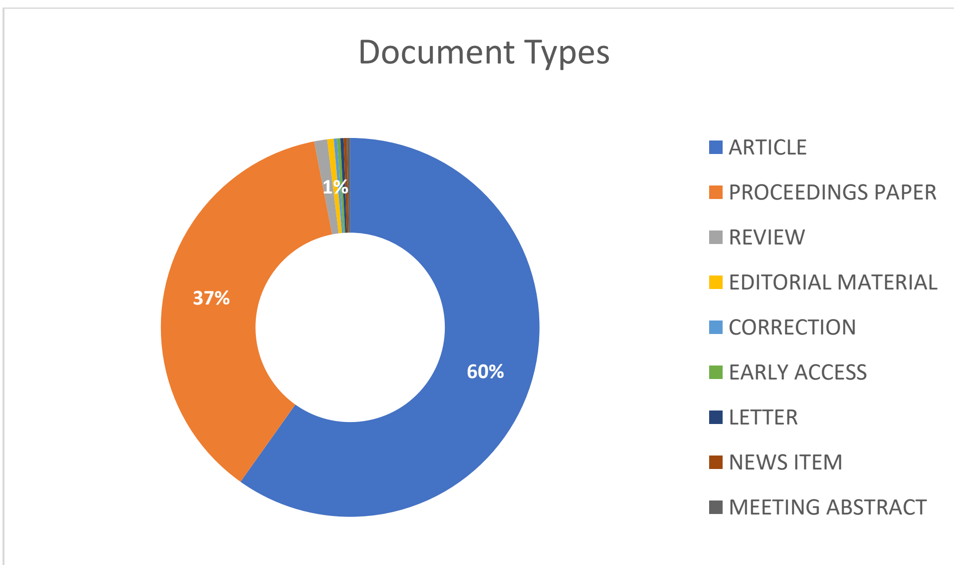

Fig. 4.6 Document types of publications from 1979 to 2020

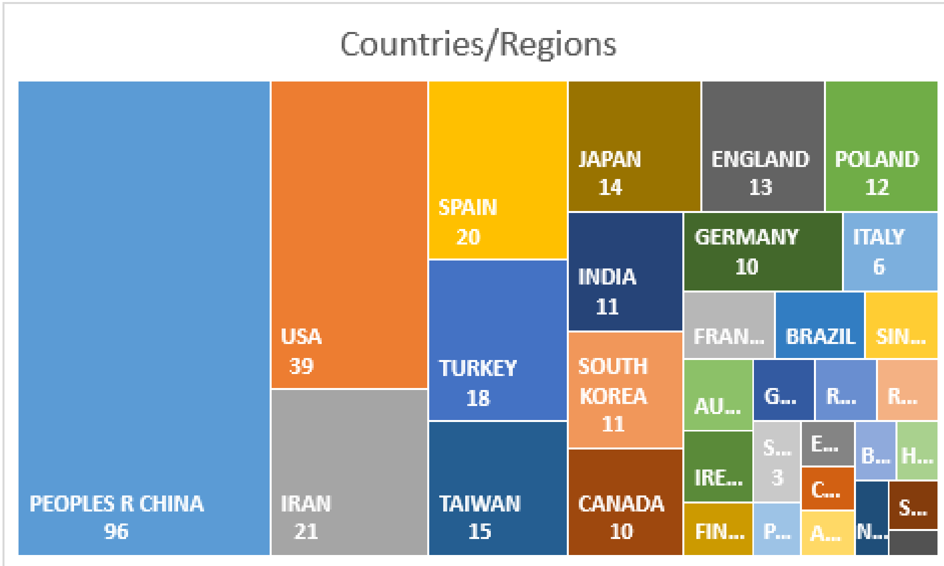

Fig. 4.7 Countries of publications from 1979 to 2020

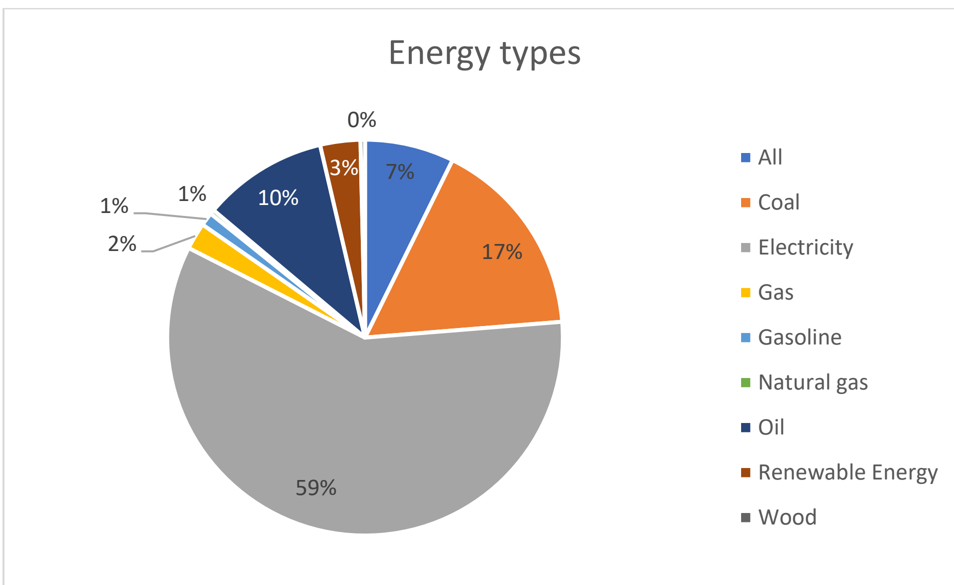

Fig. 4.8 Energy types of publications from 2000 to 2020

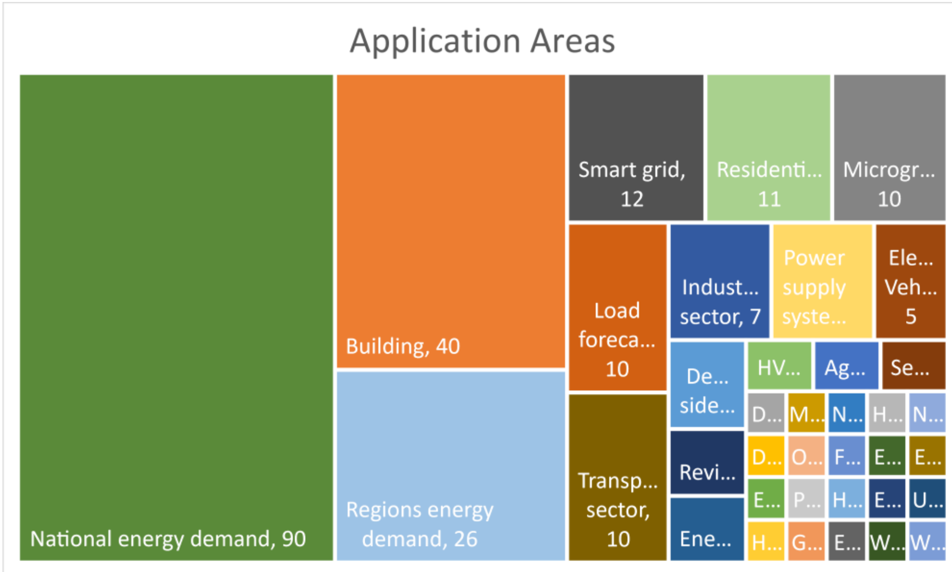

Fig. 4.9 Application areas of publications from 2000 to 2020

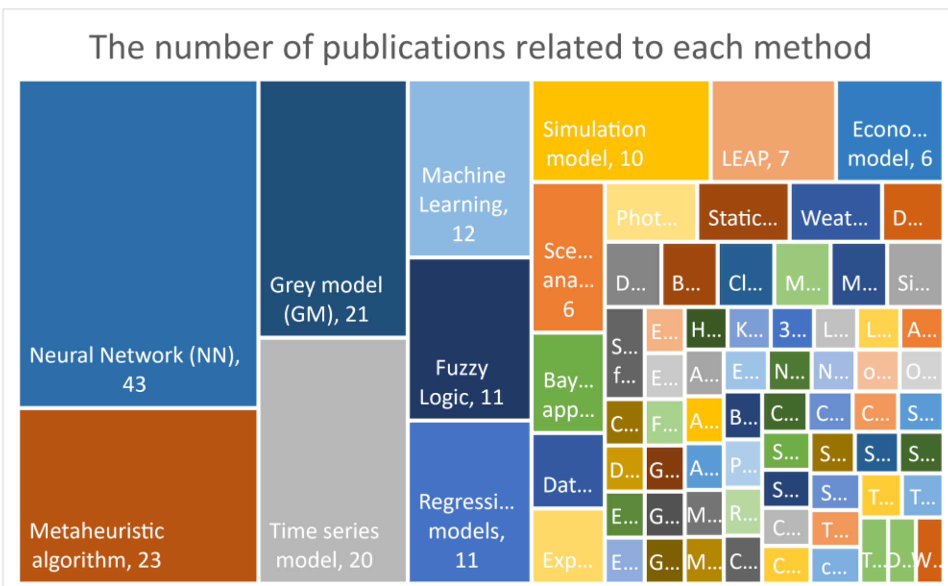

Fig. 4.10 The number of publications related to each method from 2000 to 2020

4.2.3. Classification of energy demand forecasting

Demand prediction of energy has been directed in the literature, mostly focused on three forecasting prospects (S´anchez-Dur´an et al., 2019): short-term (an hour to a week) (Nagbe, Cugliari, & Jacques, 2018; Ryu, Noh, & Kim, 2016), mid-term (a month to 5 years) (Akpinar & Yumusak, 2016), and long-term (5 to 20 years) (De Oliveira & Oliveira, 2018). Also, the heart of demand prediction of energy is the method applied for estimating (Islam et al. 2020). Forecasting methods can be considered into two types (S´anchez-Dur´an et al., 2019): data-driven approaches, whereby statistical techniques of the connection involving the demand of energy and its causal variables are certainly detected (Bourdeau, Zhai, Nefzaoui, Guo, & Chatellier, 2019); and model-driven, where this connection has been earlier recognized (Suganthi & Samuel, 2012). There is another way of categorizing the energy demand prediction approaches (Islam et al. 2020). Based on the model, for example, employing the static against the dynamic model, experimental against the mathematical model, univariate against the multivariate model, etc. In addition, based on the curve-fitting statistical technique contrasted with artificial intelligence methods (Suganthi & Samuel, 2012).

Although in the previous subsection we considered a time span of 1979–2020 to understand the bigger picture in demand forecasting of energy SC, since the number of publications per year before the year 2000 is not significant (less than five per year), in this research we focused only on publications of the last two decades from 2000 to 2020. After reviewing all publications carefully and removing duplicates, the total number of the most related publications in demand forecasting of energy was 267. Based on the literature review, in this timespan around 73 different methods of forecasting were applied by the authors. Among these methods, eight forecasting methods encompass about 56% of publications, which means they are the most used forecasting methods in the literature. We categorize these methods in Traditional (e.g. Fuzzy Logic, Grey model, Metaheuristic algorithms, Regression models, Simulation model, Time series model), and Intelligent (e.g. Machine Learning and Neural Network) models. In the following, we briefly explain each method and investigate the most cited related articles in detail.

Table 4.1. A complete list of recognized articles which used Fuzzy Logic in their forecasting methods

Year	Authors	Objective	Methods of forecasting	Energy types	Application areas	Time cited
2020	Homod et al.	Forecasting HVAC systems energy demand in real-time for Basra city	Takagi-Sugeno fuzzy	Electricity	Building	0
2018	Bock	Forecasting the energy demand of customers	fuzzy clustering	Electricity	Regions energy demand	1
2018	Pelka and Dudek	Medium-term electric energy demand forecasting	Neuro-Fuzzy System	Electricity	National energy demand	4
2018	Choudhury et al.	Renewable energy capacity estimation for Indian energy sector	Fuzzy Time Series	Coal	National energy demand	0
2017	Arcos-Aviles et al.	The design of an energy management strategy	Fuzzy Logic Control (FLC)	Electricity	Microgrid	27
2016	Bernardes et al.	Optimal energy portfolios with demand prediction and distributed generation sources	New fuzzy algorithm	Electricity	Power supply systems	0
2015	Prauzek et al.	Energy availability forecasting for harvesting-aware wireless sensor networks: analysis of energy demand of a predictor	Evolutionary Fuzzy Rules	Electricity	Harvesting-aware Wireless Sensor Networks	3

2013	Avila et al.	Fuzzy demand forecasting in a predictive control strategy for a renewable-energy based microgrid	stable Takagi & Sugeno (T&S) fuzzy model	Electricity	Microgrid	4
2012	Iranmanesh et al.	Mid-term energy demand forecasting	Hybrid Neuro-Fuzzy Models	all	National energy demand	16
2011	Kazemi et al. (a)	Forecasting agriculture energy demand: a case study of Iran	Hierarchical Fuzzy Linear Regression (FLR) Model	Oil	Agriculture Energy Demand	3
2010	Ghanbari et al. (a)	Electrical energy demand prediction	Clustering-based Genetic Fuzzy Expert System	Electricity	Load forecasting	3

4.3. Traditional methods

4.3.1. Fuzzy Logic and fuzzy sets

Fuzzy logic and fuzzy sets are used in several qualitative and vague energy utilization data to forecast energy demand (Ghalehkhondabi et al., 2017). The advantages of fuzzy sets are: stating systems rules in "if-then" forms (Iyatomi & Hagiwara, 2004), using imprecise or vague data for decisions making, coping with human cognitive procedures, investigating vagueness at several process phases (Haji and Assadi, 2009; Ustundag, Kılınç, & Cevikcan, 2010) and condensing a large amount of data into a reduced set of variable rules (Mamlook, Badran, & Abdulhadi, 2009). In contrast, the results of fuzzy approaches are not always reasonable (Hong, Lin, & Wang, 2003). A complete list of recognized articles that used Fuzzy Logic in their forecasting methods is presented in Table 4.1.

Taking into consideration a low complexity Fuzzy Logic Control (FLC), Arcos-Aviles et al. (2017) created the strategy of energy management for grid power profile smoothing. They used it in a residential grid-connected microgrid having a battery Energy Storage System (ESS) and Renewable Energy Sources (RES). Their strategy employs prediction of demand and generation to forecast the outlook microgrid's performance. Considering the Battery State-of-Charge (SOC) and the error of power forecasting, their recommended strategy achieved the right control of the grid power. In the end, they confirmed it at the Public University of Navarre (UPNa, Spain) in a real micro grid of residents. With the intention of long-term demand forecasting of energy, Iranmanesh, Abdollahzade, and Miranian (2012) suggested a hybrid approach named HPLLNF. This method includes a predictor using the local linear neuro-fuzzy (LLNF) model and a Hodrick-Prescott (HP) filter for recognizing the cyclic and trend factors in the energy demand time series. Moreover, to choose the best significant input features with the smallest probable redundancies for the forecasting method, a mutual information (MI) method was used. Their proposed method was worked out in three case studies, containing demand forecasting of natural gas, crude oil, and gasoline over the next 12 months. The gained forecasting outcomes show the notable performance of the recommended method.

Furthermore, Pelka and Dudek (2018) studied a neuro-fuzzy system for the medium-term demand forecasting of energy that involves a description of input and output variables. The authors showed yearly predictor trends of the time series to filter out the patterns and combine input data. As a numerical example, they employed the recommended method for historical data on monthly energy demand in four European countries. These results were contrasted with different methods, for instance exponential smoothing, ARIMA, and kernel regression. The high accuracy and effectiveness of the proposed method is confirmed. In another study, Avila, S´aez, Jimenez-Estevez, Reyes, and Nú˜nez (2013) investigated a stable Takagi & Sugeno (T&S) fuzzy model for demand estimating in a real-life microgrid placed in Huatacondo, Chile. For validation, the authors evaluated the proposed fuzzy model with an adaptive neural network. Besides, to improve the forecasting capability, an examination of the quantity of historical data and the rate expected for training targets was done.

4.3.2. Grey model (GM)

In the 1980s, Professor Deng Julong proposed the grey system theory, which has significant influences in the literature (Deng, 2002; Liu & Lin, 2006; Xiao, Song, & Li, 2005; Zhou & He, 2013). In general, two regular grey predicting models are the GM (1,1) and Discrete GM (1,1) models (Deng, 2002; Liu & Lin, 2006). The grey models are expressed as the systems with to some extent known and partly unknown data (Ghalehkhondabi et al., 2017). This theory chooses an ambiguous system with a ‘‘small sample and poor information’’ as the study target (Deng, 2002) and prepares dominant technical assistance for predicting and has been effectively utilized in many fields and proved acceptable outcomes (Zhou & He, 2013). A complete list of recognized articles that used the Grey Model (GM) in their forecasting methods is presented in Table 4.2. Xie, Yuan, and Yang (2015) considered China’s energy-saving policy and employed novel methods to forecast both the energy demand and supply patterns of China. To predict the trends, the authors used a novel Markov method with a quadratic programming model while to estimate the total quantity of energy demand and supply, they employed an optimized single variable discrete grey forecasting model. Their results were compared with the regression model, and it is recognized that the proposed model was slightly better than the regression in forecasting and simulating the case. Moreover, Pi et al. (2010) employed an improved grey model GM (1,1) by applying three methodologies of the 3-points average technology and the residual modification to estimate electricity demand and supply in China from 1984 to 2006. Their technique considered the general trend series and random variations. Their outcomes denoted that China’s final energy demand will rise quickly in the period 2007–2015 while it could be supplied a scientific basis for the designed development of energy production in China. Also, Hu (2017a) suggested a novel residual modification model, FLNGM (1,1). The author applied the functional-link net (FLN) along with genetic-algorithm-based learning to approximate the modification range for its corresponding projected value gotten from the original GM (1,1) model. The genetic algorithm (GA) was exploited to automatically find out the connection weights of an FLN to create the suggested FLNGM (1,1) model with high forecasting precision. To confirm the suggested model, the author exploited real energy demand cases from China. The outcomes prove that the suggested model performs well contrasted to other grey residual modification models with sign estimation.

Table 4.2. A complete list of recognized articles which used Grey model (GM) in their forecasting methods

Year	Authors	Objective	Methods of forecasting	Energy types	Application areas	Time cited
2020	Hu	Energy demand forecasting using a novel remnant GM(1,1) model	Grey models, NN	Coal	National energy demand	0
2019	Zhao et al.	Forecasting China's primary energy demand and energy structure	Rolling grey model (RGM), support vector regression (SVR), particle swarm optimization (PSO)	all	National energy demand	1
2019	Wang et al.	Prediction of the energy demand trend in middle Africa	Metabolic grey model (MGM), modified exponential curve method (MECM), autoregressive integrated moving average (ARIMA) and BP neural network model (BP)	Electricity	National energy demand	0
2018	Jiang et al.	Comparison of forecasting India's energy demand using different methods	metabolic grey model (MGM), autoregressive integrated moving average (ARIMA), MGM-ARIMA, and backpropagation neural network (BP)	Oil	National energy demand	5
2018	Ervural and Ervural	Improvement of grey prediction models and their usage for energy demand forecasting	Grey prediction models	Oil	National energy demand	3
2017	Hu (a)	Grey prediction with residual modification to energy demand forecasting	Grey prediction	Coal	National energy demand	7
2017	Hu (b)	Nonadditive grey prediction using functional-link net for energy demand forecasting	Nonadditive Grey Prediction	Coal	National energy demand	3
2017	He et al.	Research on the prediction of energy demand in China	Grey Theory and System Dynamics	Coal	National energy demand	1
2016	Hamzaçebi	Forecasting the monthly electricity demand in Turkey between 2015 and 2020	Grey forecasting model	Electricity	National energy demand	5
2016	Wang	Research on energy demand forecast in baoding city in China	Grey relational analysis, analogy method	all	Regions energy demand	0
2015	Xie et al.	Forecasting China's energy demand and self-sufficiency rate by grey forecasting model and Markov model	Grey forecasting model and the Markov model	Coal	National energy demand	70
2012	Wang et al.	China's energy demand forecasting	Grey System Theory	Coal	National energy demand	0
2012	Li et al.	Study on Beijing's energy utilization and forecast energy supply and demand	Grey model	Coal	Regions energy demand	0

2012	Wu et al.	The analysis and forecasting model of the energy supply and demand in Jiangxi province	Grey system and Brown nonlinearity exponential smoothing	Coal	Regions energy demand	0
2011	Chen-chen et al.	Energy demand forecast based on the new weakening buffer operators with exponential type	Grey model	Coal	National energy demand	1
2011	Xue-xia et al.	Energy risks zoning and demand forecasting in Jiangsu Province	Grey model	Coal	Regions energy demand	1
2011	Liming et al.	The tendency of Chinese energy demand and supply prediction	Grey Theory	Coal	National energy demand	0
2011	Shuangfeng et al.	Short-term energy demand forecasting model for small regional aspects	Gray model and multiple linear regression	Coal	Regions energy demand	0
2010	Pi et al.	Forecasting Energy Demand in China	Grey model	Electricity	National energy demand	32
2010	Lu et al.	Forecasting the motor vehicle, energy demand and CO2 emission from Taiwan's road transportation sector	Grey forecasting model	Gas	Transportation sector	1
2009	Xie and Li	Research on Gray prediction modeling optimized for energy consumption demand	Gray Prediction Modeling Optimized by Genetic Algorithm	Coal	National energy demand	3

4.3.3. Metaheuristic algorithms

The word “metaheuristic” expresses higher-level heuristics that are recommended for solving all-inclusive optimization problems (Dokeroglu, Sevinc, Kucukyilmaz, & Cosar, 2019). Metaheuristic algorithms are first created based on natural phenomena (Wang, Zhou, et al., 2020) and they denote the main research area in combinatorial optimization (Elshaer & Awad, 2020) as demonstrated by numerous literature reviews (e.g., Blum & Roli, 2003; Boussaïd et al., 2013; Gendreau & Potvin, 2005; Osman & Laporte, 1996) and books (e.g., Gendreau & Potvin 2010; Glover & Kochenberger, 2003). Regardless of the successes of the classical metaheuristic algorithms, new and novel evolutionary methods have been developed effectively in the preceding two decades as well. Investigation of metaheuristic algorithms through this period presents a considerable number of innovative metaheuristics stimulated by behavioral or evolutionary procedures. In several examples, this new trend of metaheuristic methods produces the finest resolutions for several unanswered benchmark problem sets (Dokeroglu et al., 2019). A complete list of recognized articles that used Metaheuristic algorithms in their forecasting methods is presented in Table 4.3.

In recent times, several types of research are presented by researchers to estimate the energy demand of Turkey. Ünler (2008) predicted Turkey’s demand for energy more effectively by applying the Particle swarm optimization (PSO) method. They used population, gross domestic product (GDP), import, and export as key energy demand indicators. Validation of the model was made with another metaheuristic algorithm entitled ant colony optimization (ACO). In the same way, Kiran, Ozceylan, Gunduz, and Paksoy (2012) proposed a new hybrid method to forecast energy demand of Turkey. Their hybrid method was the integration of ACO and PSO, while it developed in two fashions which were linear (HAPEL) and quadratic (HAPEQ). They considered indicators such as population, GDP, import, and export for energy demand. Moreover, a contrast was created with ACO and PSO for validation. Their results showed that relative estimation errors of the HAPE model were the lowest and the quadratic form (HAPEQ) delivered better-fit solutions because of variations of the socio-economic indicators.

To forecast China’s energy demand until 2020, Yu, Wei, and Wang (2012) proposed a network-based energy demand, predicting model by applying Mix-encoding PSO and Radial Basis Function (MPSO-RBF). The China energy demand was examined from 1980 to 2009 by considering population, GDP, the proportion of industry in GDP, the share of coal energy, and urbanization rate. The results showed that the suggested model has fewer hidden nodes and smaller estimated errors contrasted with other ANN-based forecasting models. Ghanbari, Kazemi, Mehmanpazir, and Nakhostin (2013) studied a new method named “Cooperative Ant Colony Optimization-Genetic Algorithm” (COR-ACO-GA), to build expert systems with the capability of modeling and simulating variations of energy demand. They applied the proposed model to three case studies include yearly demand for electricity, oil, and natural gas in Iran. Furthermore, they compared their outcomes to artificial neural networks (ANNs) and adaptive neuro-fuzzy inference systems (ANFISs). This comparison showed that the proposed model was more accurate-stable than other methods.

Table 4.3. A complete list of recognized articles which used Metaheuristic algorithm in their forecasting methods

Year	Authors	Objective	Methods of forecasting	Energy types	Application areas	Time cited
2019	Jalaee et al.	The modeling of the energy consumption in Iran to forecast future projections based on socioeconomic and demographic variables	Cuckoo optimization algorithm	Oil	National energy demand	0
2018	Kampelis et al.	Development of demand response energy management optimization at building and district levels	Genetic Algorithm and Artificial Neural Network Modelling	Electricity	Building	10
2017	Hu (c)	Energy demand forecasting	Genetic-algorithm-based remnant Grey prediction model	Coal	National energy demand	7
2017	Badar-Ul-Islam et al.	Electrical energy demand prediction in smart grid	Chaotically improved meta-heuristics and modified BP neural network-based model	Electricity	Smart grid	9
2016	Nazari and Kazemi	Select the best scenario for energy demand forecast of residential and commercial sectors in Iran by using particle swarm optimization algorithm	Particle swarm optimization (PSO) algorithm	Oil	Residential	0
2016	Chen et al.	Predict the energy demand of greenhouses with a better performance of accuracy and cost time	Adaptive particle swarm optimization, genetic algorithms (APSO-GA)	Electricity	Greenhouses	20
2016	Liu et al.	Prediction of primary energy demand in China	Adaptive Genetic Algorithm Energy Demand Estimation (AGAEDE) optimal model	Coal	National energy demand	8
2016	Nazari et al.	Forecasting of energy demands of residential and commercial sectors in Iran using linear and exponential functions	Genetic and Particle swarm optimization (PSO) algorithms	Electricity	Residential	2
2015	Uguz et al.	Determine Turkey's long-term energy demand	Artificial Bee Colony with Variable Search Strategies (ABCVSS) method	Oil	National energy demand	1
2015	Nazari et al.	Develop different models to analyze energy demand of residential and commercial sectors in Iran	The GA and PSO energy demand estimation models (GA-DEM, PSO-GEM)	Oil	Residential	6
2014	Cao et al.	Energy demand forecasting based on economy-related factors in China	Support machine regression and quantum-behaved particle swarm optimization	Coal	National energy demand	6
2013	Ghanbari et al.	Model and simulate fluctuations of energy demand under the influence of related factors	Cooperative Ant Colony Optimization-Genetic Algorithm (COR-ACO-GA)	all	National energy demand	40

2013	Cheng	Energy demand forecast of the city	Cellular genetic algorithm	Coal	Regions energy demand	0
2012	Baczynski and Piotrowski	Description of a worked-out method of estimating hourly demand electric energy forecasts quality for chosen consumers groups	Particle swarm optimization algorithm (PSO)	Electricity	Regions energy demand	0
2012	Yu and Zhu	Energy demand forecasting in China	A hybrid algorithm called PSO-GA (particle swarm optimization-genetic algorithm)	Coal	National energy demand	35
2012	Kiran et al.	Forecasting energy demand of Turkey	A hybrid approach based on Particle Swarm Optimization and Ant Colony Algorithm	Oil	National energy demand	111
2012	Yu et al.	China's primary energy demands in 2020	Mix-encoding Particle Swarm Optimization and Radial Basis Function (MPSO-RBF) estimation model	Coal	National energy demand	40
2012	Piltan et al.	Energy demand forecasting in Iranian metal industry	Linear and nonlinear models based on evolutionary algorithms	Electricity	Industrial sector	34
2012	Assareh, et al.	Forecasting energy demand in Iran	Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) Methods	Oil	National energy demand	11
2012	Forouzanfar et al.	Transport energy demand forecasting	Multi-level genetic programming	Oil	Transportation sector	21
2010	Parol and Piotrowski	Long-term forecasting method of annual electrical energy demand in electric distribution companies	Prigogine logistic equation aided by evolutionary algorithms	Electricity	Power supply systems	0
2010	Ghanbari et al. (b)	Prediction of electrical energy demand	Hybridization of Particle Swarm Optimization and Noise Filtering	Electricity	National energy demand	3
2008	Uenler	Energy demand forecast: The case of Turkey with projections to 2025	Particle swarm optimization (PSO)	Oil	National energy demand	128

4.3.4. Regression models

One of the best universally applied statistical techniques for predicting energy demand is Regression models (Islam et al. 2020). There are two common types of Regression: Linear and Nonlinear (for more details about the categorization of regression models follow Fumo & Rafe Biswas, 2015; Sobri, Koohi-Kamali, & Rahim, 2018). Regression methods set up a predicting function by determining a dependent variable value (known as the response variable) based upon one or more independent variables (known as a predictor variable) (Abdul-Wahab, Bakheit, & Al-Alawi, 2005; Ghalehkhondabi et al., 2017). A complete list of recognized articles that used Regression models in their forecasting methods is presented in Table 4.4.

Some key elements affect a building's heat utilization, such as the house global heat loss coefficient (G), the south equivalent surface (SES), and the dissimilarity among the inside set point temperature and the sol–air temperature. Accordingly, Catalina, Iordache, and Caracaleanu (2013) suggested a model to forecast the demand for heating energy by applying a multiple regression forecasting method. The authors used a multiple dynamic simulation to define the values of the inputs/output data of the forecasting method. They used real data from 17 blocks of apartments for validation. Using a complete error analysis, the proposed method offered an exceptionally good accuracy with a correlation coefficient of 0.987. Another study by Zhang, Mu, Li, and Ning (2009) applied the partial least square regression (PLSR) technique with two situations to estimate the energy demand for transportation for 2010, 2015, and 2020. The authors investigated Transport energy demand for the period of 1990–2006 considering GDP, urbanization rate, passenger-turnover, and freight-turnover. Their results were remarkably close to the prediction of the Energy Research Institute of China. Additionally, to assess power and heat load profiles for several house types, Pedersen, Stang, and Ulseth (2008) proposed a load forecasting technique. The authors employed a regression analysis for the heat load model while different statistical distributions were used for the power load model. Consequently, they utilized an approach for load collection based upon the house types' load profiles to forecast the highest load demands, load length profiles, annual load profiles, and annual energy demands, all allocated into power and heat objectives, for a scheduling zone.

Table 4.4. A complete list of recognized articles which used Regression models in their forecasting methods

Year	Authors	Objective	Methods of forecasting	Energy types	Application areas	Time cited
2019	Amin et al.	Analysis and demand forecasting of residential energy consumption	Linear regression models	Electricity	Residential	0
2017	Taniguchi et al.	Define impact on consumers' utility and propose two demand response methods which aim to minimize the impact	Linear regression	Electricity	Smart grid	0
2017	Dudek and Pelka	Medium-term electric energy demand forecasting using Nadaraya-Watson Estimator	Nonparametric regression: Nadaraya-Watson Estimator	Electricity	Power supply systems	2
2013	Mestekemper et al.	Forecasting energy demand at an intraday resolution	Semiparametric regression smoothing	Electricity	Regions energy demand	14
2013	Catalina et al.	Fast prediction of the heating energy demand	Multiple regression model	Electricity	Building	90
2013	Feng et al. (a)	Study on China's energy demand	Regression prediction based on path analysis	Coal	National energy demand	0
2012	Hong and Wang	Discuss three aspects of demand response through a case study of a US utility	Regression-based approach	Electricity	Load forecasting	3
2009	Taghizadeh et al.	Forecasting transport energy demand: a case study of Iran	Multi-level Fuzzy linear regression model	Oil	Transportation sector	0
2009	Zhang et al.	Forecasting the transport energy demand in China	Partial least square regression (PLSR)	Coal	Transportation sector	87
2009	Hida et al.	Load Forecasting on demand side for operation of battery energy storage system	Multi-Regression Model	Electricity	Load forecasting	0
2008	Pedersen et al.	Load prediction method for heat and electricity demand in buildings	Regression analyses	Electricity	Building	87

4.3.5. Simulation model

A simulation takes a model to live and demonstrations in what way an entity or incident will work (Systems Engineering Fundamentals 2003). A simulation model can be functioned in a prediction mode through studying the historical detected values of the model outcome (Tongal & Booij, 2018). A steady-state simulation presents facts about the system at a precise instant in time (typically at equilibrium, if such a state occurs). A dynamic simulation presents information over time (Daniel, Ebhora, Johnson, & Ugochukwu, 2013). Simulation helps researchers employ mutually qualitative and quantitative intelligence to develop their simulation and estimation (Pasinski, 2018). A complete list of recognized articles that used the Simulation model in their forecasting methods is presented in Table 4.5.

With the purpose of investigating the energy of a building, Cho, Shin, Kim, and Hong (2014) estimated the energy utilization features of HVAC&R systems. The authors aimed to exploit an energy estimation procedure and a simple simulation program. Engineers and designers could apply this program to evaluate the efficiency and economic gains of HVAC&R systems. Their procedure of energy analysis showed up how to plan and drawing for employing the most useful HVAC&R systems. Also, Obara, Morizane, and Morel (2013) proposed a simulation model to predict electric power and heat demand by using weather data and equivalent values. They aimed to schedule the storage of electricity and heat from midnight to early morning. They used some case studies, and their results showed the effect of the economic productivity of the heating system, the volume of the tidal power generator, the insulation efficiency (Q-value) on the energy cost, and the forecasting error of the tidal power generator. Furthermore, they optimized the suggested simulation model with the objective functions of cost-reducing (facilities and operation) of the model. Another research by Grueger, Robinius, Hoch, Stolten, and Hartmann (2019) proposed an intelligent operating policy based on a simulation model considering imperfect predictions (e. g. of energy fees or wind obtainability) and non-linear electrolyzer performance. Their outcomes indicate that this approach cut down hydrogen production costs by up to 9.2% and boosts wind energy utilization by up to 19%, correspondingly.

Table 4.5. A complete list of recognized articles which used Simulation model in their forecasting methods

Year	Authors	Objective	Methods of forecasting	Energy types	Application areas	Time cited
2019	Forouzandeh, and Richter	Accurate prediction of the heating energy demand of courtyard's surrounding envelopes	Temperature correction factor	Electricity	Building	0
2019	Grueger et al.	Optimized electrolyzer operation: employing forecasts of wind energy availability, hydrogen demand, and electricity prices	Simulation model	Electricity and wind	Fuel cell-based mobility	7
2018	Filippov et al.	A description of the computer-based energy demand forecasting system (EDFS)	Adaptive simulation models	Electricity	Regions energy demand	0
2017	Naoi et al.	Demand and supply simulations considering detailed forecast, scheduling and control functions for Japanese power system with a massive integration of renewable energy sources	Simulation model	Electricity	National energy demand	0
2017	Silenzi et al.	Energy demand modeling and forecast of Monoblocco building at the city hospital of Genova	Dynamic simulations	Electricity	Building	0
2017	Torres-Sanz et al.	Prediction of electric vehicles energy demand	Simulation	Electricity	Electric Vehicles	0
2016	Chu et al.	Optimal integration of alternative energy sources in production systems with customer demand forecast	Discrete-event simulation	Renewable Energy	Industrial sector	5
2014	Cho et al.	Development of an energy evaluation methodology to make multiple predictions of the HVAC&R system	Simulation	Electricity	HVAC energy demand	23
2014	Zhang et al.	Dynamic power demand prediction for battery-supercapacitor hybrid energy storage system	Simulation	Electricity	Electric Vehicles	2
2013	Obara et al.	Study on the method of electricity and heat storage planning based on energy demand and tidal flow velocity forecasts for a tidal microgrid	Simulation model	Electricity	Microgrid	10

4.3.6. Time series model

Documenting the order of the values of a variable at consecutive equally spaced points in time produces a time series. Forecasting the upcoming values of a variable based upon the earlier detected values is called Time-series predicting (Hamilton, 1994). A normal illustration of time series is the crude oil price documented at fixed time-spaces, which are employed to forecast the prospect price of the crude oil (Ghalehkhondabi et al., 2017). Time series prediction is a wide and dynamic research topic that has obtained significant consideration from the wide type of disciplines, for instance engineering, business, statistics, etc. Hence, the majority of the literature has concentrated on methods that can get precise predictions in many real-world purposes (Hajirahimi & Khashei, 2019). A complete list of recognized articles that used the Time series model in their forecasting methods is presented in Table 4.6.

In Turkey, many of the experimental research studies include different methods of econometric modeling. Conversely, because the projected economic and demographic parameters regularly differ from the realizations, time-series forecasting provides superior outcomes. Consequently, Ediger and Akar (2007) forecasted the main energy demand of Turkey from 2005 to 2020 by using both the Autoregressive Integrated Moving Average (ARIMA) and seasonal ARIMA (SARIMA) approaches. The forecasting results of ARIMA are illustrated to be more consistent than the whole of the individual predictions. Furthermore, the authors suggested several strategies based on their results. Some countries such as China and India meet with various challenges about forecasting their energy demand. To better meet these future problems, they can employ improved forecasting of energy demand along with updated upcoming global energy requirements. Accordingly, Wang, Lv, and Zeng (2018), with the aim of more precisely predicting energy demand in China and India, applied some time series forecasting techniques including single-linear, hybrid-linear, and non-linear. To measure the superiority of these suggested methods, the authors employed three standards (trend map, error measure, and fit method). The outcomes presented showed that their recommended methods have an extremely high degree of fit, a little error rate, and great fitting accuracy. Another paper by Lora, Santos, Santos, Exp´osito, and Ramos (2004) studied a 24-h load prediction problem by applying a time-series forecasting technique based upon the kNN method to the Spanish transmission system. Moreover, a different model was set up based on recorded data through a typical dynamic regression method, while the parameters were approximated by solving a least-squares problem.

Table 4.6. A complete list of recognized articles which used Time series model in their forecasting methods

Year	Authors	Objective	Methods of forecasting	Energy types	Application areas	Time cited
2020	Salam et al.	Estimate and forecast the number of houses and the resultant energy consumptions in Brunei Darussalam	Spline interpolation, autoregressive integrated moving average (ARIMA) model, nonlinear autoregressive (NAR) neural network.	Electricity and water	Building	0
2019	Sanchez-Duran et al.	Forecasting energy demand for Spain	Time-series techniques	Oil	National energy demand	0
2019	Chen et al.	The long-term forecast of energy demand and uncertainty evaluation with limited data for energy-imported cities in China	Autoregressive Integrated Moving Average, Vector Autoregressive models, Monte Carlo method	Coal	Regions energy demand	0
2018	Chen and Huang	Forecasting China's primary energy demand	Autoregressive distributed lag (ARDL) bounds testing approach and an adaptive genetic algorithm (AGA)	Coal	National energy demand	0
2018	Wang et al. (a)	Forecasting energy demand in China and India	Single-linear, hybrid-linear, and non-linear time series, grey theory	Oil	National energy demand	29
2018	Gao et al.	Optimal scheduling and real-time control schemes of battery energy storage system for microgrids	The autoregressive integrated moving average (ARIMA)	Electricity	Microgrid	5
2017	Rehman et al.	Forecasting long-term energy demand in Pakistan	Autoregressive Integrated Moving Average (ARIMA), Holt-Winter, the long-range alternative energy planning (LEAP)	all	National energy demand	14
2016	Adom et al.	Forecasting demand and investigate the shift in price and income elasticities and the persistent profile of shocks for diesel and gasoline fuels in the road transport sector	The structural cointegration VAR	Gasoline	Transportation sector	8
2016	Rahman et al.	Forecasting the long term energy demand of Bangladesh using SPSS from 2011-2040	Time-series model with SPSS	Electricity	National energy demand	0
2016	El Kafazi et al.	Modeling and Forecasting energy demand in Morocco	Auto-Regressive Integrated Moving Average (ARIMA)	Electricity	National energy demand	5
2015	Hao, and Yang	Forecasting and analysis of renewable energy demand in the rural areas of China	VAR model	Renewable Energy	Regions energy demand	0
2014	Wang et al.	Presenting a methodology to systematically formulate a hybrid renewable energy system (HRES)	Autoregressive (AR) model	Electricity	Residential	9

2014	Haibo and Wei-feng	Research on energy optimal scheduling based on supply and demand forecast for iron and steel enterprises	Time-series model	Electricity	Industrial sector	0
2014	Haitao et al.	Spatial characters of energy demand in China	Time-series forecasting methods	Coal	National energy demand	0
2012	Pan et al.	Forecast energy demand in Taiwan's electronic parts and components manufacturing industry	SARIMA models	Electricity	Industrial sector	1
2011	Chuanping et al.	The prediction to Chinese energy demand in 2020	Visual Angle of Time Series Analysis	Coal	National energy demand	0
2008	Xu	Forecasting China energy demand up to the year 2020	Vector Autoregression Model	Oil	National energy demand	0
2007	Ediger and Akar	Forecasting of primary energy demand by fuel in Turkey	ARIMA, SARIMA	Oil	National energy demand	245
2006	Contreras and Santos	Short-term demand and energy price forecasting	Time-series procedures, Artificial Intelligence	Electricity	Electric energy markets	3
2004	Lora et al.	Application to the short-term electric energy demand	Time-series prediction	Electricity	Load forecasting	22

4.4. Intelligent methods: demand forecasting in the era of Industry 4.0

Since the fourth industrial revolution and the digitization of SCs, businesses recognize that the implementation of Industry 4.0 solutions produces competitive advantages and opportunities for added sustainable management. Therefore, Real-time data gathering and predictive analytics through big data analytics, cloud manufacturing, Artificial Intelligence (AI), deep learning, Internet-of-Things (IoT), simulation and forecasting methods are exploited. These methods deal with the modern requirements of SCs for example, flexibility, improved productivity, less waste, superior forecasting of market demand, resources optimization inside and outside an industrial unit and further sustainable manufacture procedures of SCs (Mastos et al., 2020).

In the past decades, several traditional models have been regularly utilized for energy demand prediction (Chen, Rao, Liu, et al., 2019). These methods need labor-intensive work, including collecting, compiling, and using data, often in spreadsheets. Since the volume of data is increased, traditional models have turned out to be unmanageable and time-consuming methods that result in unaware biases. On the other hand, in the area of Industry 4.0, there's an alternative approach. Companies are transferring to predicting procedures that engage employees to work out symbiotically through data-fueled, predictive algorithms. It is all made achievable with novel technologies such as AI tools. Employing these technologies through expert prediction provides enterprises the capability to determine issues they need to know about, along with issues they didn't know, with more assurance as well as speed (Hogan & Merrill, 2019).

In Industry 4.0, AI is a division of computer science which is a technology that considers human logical judgment, group behavior, and reasoning with computer simulation (Ciulla, D'Amico, Lo Brano, & Traverso, 2019). AI can be denoted as "programs, systems, algorithms, and machines that express intelligence" (Shankar, 2018), which seems like "intelligent human behavior" (Pantano & Pizzi, 2020; Syam & Sharma, 2018). AI applications are vast, and it has obtained significant attention throughout the previous decade. AI applications in the area of predicting and a number of studies have been performed by employing Machine Learning (ML) techniques and Neural Networks (NNs) (Makridakis, Spiliotis, & Assimakopoulos, 2018), as well as support vector regression (SVR) machine-based models, and random forest (RF) (Wei, Li, Peng, Zeng, & Lu, 2019) to enhance time-series forecasting. Furthermore, AI-based predictive models have been employed to determine prediction of energy demand (Casteleiro-Roca, G´omez- Gonz´alez, Calvo-Rolle, Jove, Quinti´an, Martín, & M´endez-Perez, 2018; Casteleiro-Roca et al. 2018; Khosravani, Castilla, Berenguel, Ruano, & Ferreira, 2016; Shao et al., 2017; Singh & Khatoon, 2013; Suganthi & Samuel, 2012; Torres, Aguilar, & Zu˜niga-Meneses, 2018).

On the contrary with traditional methods, AI-based forecasting methods do not depend on the definite association among energy demand and its affecting factors while learning after a huge quantity of historical data for the forecasting as an alternative (Wang, Jiang, Zhou, Wu, & Qin, 2016). The key success factors of AI are based on the exploitation of algorithms skilled in learning through trial and error and enhancing their performance over time (Makridakis et al., 2018). These methods have robust qualifications in treating nonlinear problems and so broadly exploited in energy demand forecasting, mainly in short-term forecasting (Wei et al., 2019; Yang, Yan, & Lam, 2014). Furthermore, AI methods application is particularly effective in conditions where a proper mathematical problem of energy consumption is not clear (Islam et al. 2020). The fact is that since 2015 the number of research studies that employed intelligent methods for energy demand forecasting increased sharply (see Fig. 4.11). Consequently, in the next subsections, we briefly investigate the two most cited intelligent methods of energy demand forecasting in the literature including ML techniques and NNs.

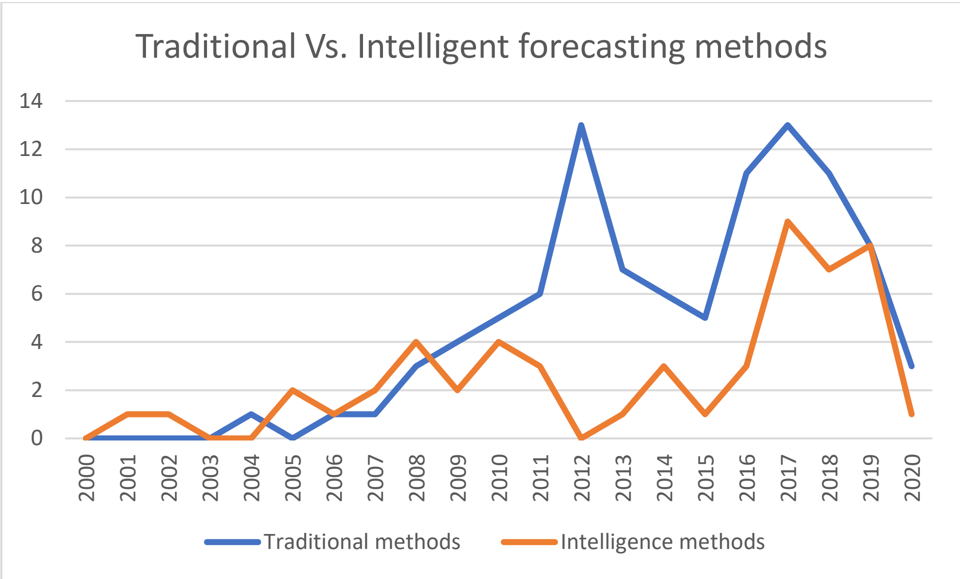

Fig. 4.11 The trends of forecasting methods from 2000 to 2020

4.4.1. Machine learning

In the scholarly literature for time series prediction, ML approaches have been recommended as replacements to statistical ones (Makridakis et al., 2018). The ML obtains regulations of decisions from a chain of existing objective information and with learning and assessment of chains of input and output consequences, revealing the core mechanism (Wang, Zeng, Dai, & Zhu, 2020). The purpose of ML approaches is to enhance forecasting precision by diminishing some loss function, usually the sum of squared errors. ML approaches are computationally further demanding than statistical ones, needing more dependent on computer science to be applied, finding them at the intersection of statistics and computer science (Makridakis et al., 2018). A complete list of recognized articles that used ML in their forecasting methods is presented in Table 4.7.

Considering building heating energy, Guo et al. (2018) developed an energy demand forecasting model by using ML approaches. Their models involved extreme learning machine, backpropagation neural networks, support vector regression, and multiple linear regression. Also, they considered the correlation analysis technique to optimize various meteorological factors, operating parameters, time, and indoor temperature parameters in the function of model variables. To evaluate the functioning of the proposed models, real data of building heating with a ground source heat pump system were gathered. Outcomes confirmed that for various ML approaches, the operations of extreme learning machine models were better than others. In the same year, Ahmad and Chen (2018a) forecasted the required upcoming energy of water source heat pumps by using four ML-based models which were CDT, FitcKnn, LRM, and Stepwise-LRM. They considered input factors that involve environmental data, power consumption data of the water source heat pump, hour-type/day-type, while the output was the net electricity consumption of the water source heat pump. To confirm the precision of the proposed models, four validation approaches such as the LMA, BRNN, GPR, and TB were utilized. In another study by Ahmad and Chen (2018b), they suggested an energy forecasting model for medium and long-term district level by employing a new ML-based model includes

1) artificial neural network with nonlinear autoregressive exogenous multivariable input model; 2) multivariate linear regression model; and 3) adaptive boosting model. For the model's input/output, they considered environmental and aggregated energy consumption data, respectively. The forecasting results showed that not only the proposed model could improve the accuracy of forecasting but give suitable forecasting intervals in the smart grid environment.

Table 4.7. A complete list of recognized articles which used Machine Learning in their forecasting methods

Year	Authors	Objective	Methods of forecasting	Energy types	Application areas	Time cited
2019	Yuan et al.	Prediction-based microgrid energy management strategy	Hybrid prediction-based energy management strategy	Electricity	Microgrid	2
2019	Huang et al.	Energy demand prediction strategy for residential buildings	Ensemble learning methods	Electricity	Building	2
2019	Kim et al.	Development of a consecutive occupancy estimation framework for improving the energy demand prediction performance of building energy modeling tools	Machine learning	Electricity	Building	4
2019	Eseye et al.	Improved electricity demand forecasting in decentralized energy systems	Machine Learning	Electricity	Decentralized energy system	1
2018	Guo et al.	Energy demand prediction for building heating systems	Machine learning	Electricity	Building	27
2018	Ahmad and Chen (b)	Forecasting district level medium-term and long-term energy demand in the smart grid environment	Machine-learning models	Electricity	Smart grid	9
2018	Ahmad, and Chen (a)	Forecasting the future energy requirement of water source heat pumps	Machine learning-based models	Electricity	Water source heat pumps	10
2017	Guo et al.	A thermal response time ahead energy demand prediction strategy for building heating system	Machine-learning methods	Electricity	Building	2
2017	Paterakis et al.	Aggregated energy demand prediction	Deep Learning Versus Traditional Machine Learning Methods	wind, solar	Regions energy demand	0
2017	Minhas et al.	Load control for supply-demand balancing under renewable energy forecasting	Support Vector Machine (SVM) learning algorithm	Electricity	Smart grid	1
2015	Zhang and Jing	The prediction of cement energy demand	Support vector machine	Electricity	Industrial sector	1
2010	Frankowski et al.	Prediction the electricity demand and the electrical energy balance differences in Poland	Advanced machine learning algorithms	Electricity	National energy demand	0

4.4.2. Neural network (NN)

NNs are most distinguished for being appropriate to predict the future values of nonlinear data sets, peer processing to effectively execute the various immediate tasks, and the flexibility to many environmental circumstances which is the consequence of their learning structures (Chen, Lai, & Yeh, 2012). The Artificial NN (ANN) is considered as a data-driven method stimulated through the human brain. It is created by a system of processing nodes (or neurons), which carry out numerical operations and are interrelated in a definite order (Ghalehkhondabi et al., 2017). ANN is a structure for several different ML algorithms to run mutually and deal with difficult data records (Wei et al., 2019). The ANN employed data to recognize the relation of input and output variables and estimate the outputs of the noisy multivariate time series (Adamowski, Fung Chan, Prasher, Ozga-Zielinski, & Sliusarieva, 2012). The ANN-based methods employed in energy demand prediction consist of the feedforward neural network (FFNN) (Azadeh, Babazadeh, & Asadzadeh, 2013; Jebaraj, Iniyan, & Goic, 2011; Kermanshahi, 1998; Soldo, Potoˇcnik, ˇSimunovi´c, ˇSari´c, & Govekar, 2014), BPNN (Yu & Xu, 2014), adaptive network-based fuzzy inference system (ANFIS) (Azadeh et al., 2011; Azadeh et al., 2013), wavelet neural network (WNN) (Bhaskar & Singh, 2012; Catal˜ao, Pousinho, & Mendes, 2011; Zhang, Wei, Li, Tan, & Zhou, 2018; Zhang & Wang, 2012), ESN (Bianchi, Santis, Rizzi, & Sadeghian, 2015; Wang et al. 2018c), deep learning (DL) models, and others (Burger & Moura, 2015; Jiang, Liu, & Song, 2017; Lopez, Valero, Senabre, Aparicio, & Gabaldon, 2012; Lu, Wang, Cai, & Zhao, 2015). A complete list of recognized articles that used Neural Network (NN) in their forecasting methods is presented in Table 4.8.

Gonz´alez-Romera et al. (2006) predicted the monthly demand of electricity in Spain by applying two NNs. They used some models in the movement extraction to observe which of them delivers the best results. Their outcomes were superior to other methods, especially when only one NN was employed to predict the first consumption series. After that, Yokoyama, Wakui, and Satake (2009) proposed a new global optimization method named "Modal Trimming Method" to recognize the parameter quantities of a model for non-linear programming problems. At first, they detached the trend and periodic variation of energy demand historical data, then the transformed data is manipulated as the key input to a NN. Additionally, air temperature and relative humidity were counted as further inputs to the NN, and their consequence on the forecasting of energy demand was examined. For a benchmark test, they applied the proposed model to forecast the cooling demand in a building and its effectiveness and validity were explained as well. By focusing on a medium-term energy demand predicting system, Srinivasan (2008) tried to assist utilities to recognize and predict the demand of energy for each of the end-use utilization segment of the energy system, characterizing residential, manufacturing, business, non-industrial, show business and public lighting load. The author has applied several conventional and NN-based approaches to estimate the monthly demand for energy. Based on the results, ANN-based models were superior, especially the cluster technique of data handling (GMDH) neural network.

Table 4.8. A complete list of recognized articles which used Neural Network (NN) in their forecasting methods

Year	Authors	Objective	Methods of forecasting	Energy types	Application areas	Time cited
2020	Vesa et al.	Energy flexibility prediction for data center engagement	Neural Network (NN)	Electricity	Data centers (DCs)	0
2019	Pramono et al.	Short-term load forecasting (STLF)	Causal residual convolutional neural network (CNN) and long short-term memory (LSTM)	Electricity	Load forecasting	0
2019	Feng et al.	Proposing a distributed hour-ahead energy trading management is	Neural Network (NN)	Electricity	Microgrid	0
2019	Pelka and Dudek	Forecasting monthly energy demand for four European countries	Generalized Regression Neural Network	Electricity	Regions energy demand	1
2019	Casteleiro-Roca et al.	Short-term energy demand forecast in hotels	Artificial Neural Network, Support Vector Regression	Electricity	Hotels	0
2018	Yin et al.	Comprehensive forecast of urban water-energy demand	Artificial neural network model	water	Regions energy demand	5
2018	Cao et al.	Conditional density forecast of China's energy demand	Quantile regression neural network (QRNN)	Coal	National energy demand	1
2018	Mason et al.	Forecasting energy demand, wind generation, and carbon dioxide emissions in Ireland	Evolutionary neural networks	Electricity and wind	National energy demand	11
2018	Muralitharan et al.	Energy demand prediction in smart grid	Neural network	Electricity	Smart grid	43
2017	Labidi et al.	A new strategy based on power demand forecasting to the management of multi-energy district boilers equipped with hot water tanks	Wavelet-based Multi-Resolution Analysis combined with Artificial Neural Networks	wood, gas	Multi-energy district bOilers	6
2017	Ahmad et al.	Energy demand prediction for large non-domestic buildings	Random Neural Network Predictor	Electricity	Building	0
2017	Kumar et al.	Ensemble wavelet learners for demand forecasting in energy grids India	Neural network, nonlinear autoregressive exogenous model (NARX)	Electricity	Smart grid	0
2017	Hu and Jiang	Forecasting energy demand using neural-network-based grey residual modification models	Neural-network-based grey residual modification models	Electricity	Regions energy demand	17
2017	Das G.S.	Forecasting the energy demand of Turkey	Neural network based on the particle swarm optimization algorithm with mutation (PSOM-NN)	Oil	National energy demand	3

2017	Kankal and Uzlu	Modeling and forecasting long-term electric energy demand in Turkey	Artificial neural network (ANN) with teaching-learning-based optimization (TLBO)	Electricity	National energy demand	18
2017	Furukakoi et al.	Optimum capacity of energy storage system considering solar radiation forecast error and demand response	Neural Network (NN)	Electricity	Power supply systems	0
2016	Sanjari et al.	Studying the demand forecast error and a near-optimal dispatch strategy by using an artificial neural network (ANN) is proposed for the residential energy system	Artificial neural network (ANN)	Electricity	Residential	21
2016	Deka et al.	Predictive modeling techniques to forecast energy demand in the United States: a focus on economic and demographic factors	Artificial neural network (ANN) models, regression analysis models, autoregressive integrated moving average (ARIMA)	all	National energy demand	8
2016	Zhao N.	Study on the prediction of energy demand based on master-slave neural network	Master-Slave Neural Network	Electricity	National energy demand	0
2015	Tianheng et al.	A supervisory control strategy for plug-in hybrid electric vehicles	Neural network model	Electricity	Electric Vehicles	52
2014	Zhang and Li	Forecasting Chinese energy supply and demand situation	Backpropagation (BP) neural network	all	National energy demand	1
2014	Es et al.	Predicting the net energy demand of Turkey	Artificial neural networks (ANN)	Oil	National energy demand	10
2014	Ardakani and Ardehali	Investigating the effects of historical DSM data on the accuracy of EEC modeling and long-term forecasting	Artificial neural network (ANN) models, improved particle swarm optimization (IPSO), shuffled frog-leaping (SFL) algorithms	Electricity	Demand-side management	43
2013	Feng et al. (b)	Predicting China's energy demand	RBF neural network model	Coal	National energy demand	0
2011	Kazemi et al. (b)	Residential and commercial energy demand forecast: Iran case study	Multi-level Artificial Neural Network	Oil	Residential	2
2011	Zhang et al.	Energy demand forecasting in China	Dynamic RBF Neural Network	Coal	National energy demand	0
2011	Filik et al.	Hourly forecasting of long term electric energy demand	Mathematical models and Artificial Neural Network (ANN)	Electricity	National energy demand	10
2010	Kazemi et al.	Annual transport energy demand forecasting by several socio-economic indicators	Artificial neural networks (ANNs) model	Oil	Transportation sector	6
2010	Kolokotroni et al.	Prediction of heating and cooling energy demand for buildings in London	Artificial Neural Network (ANN)	Electricity	Building	51

2010	Meng et al.	Monthly electric energy demand forecasting under the influence of two calendars	RBF neural network	Electricity	National energy demand	0
2009	Yokoyama et al.	Prediction of energy demands using a neural network	Neural network	Electricity	Building	81
2009	Wang and Liang	The forecast for energy demand	Artificial Neural Network	Coal	National energy demand	2
2008	Ruas et al.	Electrical energy demand prediction	Artificial Neural Networks and Support Vector Regression	Electricity	Load forecasting	0
2008	Srinivasan D.	Energy demand prediction using GMDH networks	group method of data handling (GMDH) neural network	Electricity	Sectorial energy demand	78
2008	Gonzalez-Romera et al.	Monthly electric energy demand forecasting	Neural networks and Fourier series	Electricity	National energy demand	55
2008	Abdel-Aal, R.E.	Univariate modeling and forecasting of monthly energy demand	Abductive and neural networks	Electricity	National energy demand	50
2007	Gonzalez-Romera et al.	Forecasting of the electric energy demand trend and monthly fluctuation	Neural networks	Electricity	Power supply systems	31
2007	Ungureanu et al.	Simulation and prediction of the thermal energy demand of buildings	Statistical methods and artificial neural networks	Electricity	Building	0
2006	Gonzalez-Romera et al.	Monthly electric energy demand forecasting based on trend extraction	Neural networks	Electricity	National energy demand	112
2005	Thaler et al.	Prediction of energy consumption and risk of excess demand in a distribution system	Empirical model	Gas	National energy demand	14
2005	Yokoyama et al.	Prediction of energy demands	Neural network	Electricity	Building	1
2002	Carmona et al.	Predicting the evolution of the monthly demand of electric consumption	Neural networks	Electricity	Load forecasting	5
2001	Olofsson and Andersson	Long-term energy demand predictions based on short-term measured data	Neural network	Electricity	Building	33

Table 4.9. Summary of the most used forecast methods of energy demand (Zhao et al. 2019, Wang et al. 2018a; Yuana et al. 2017)

Forecast model	Data requirement	Forecast period	The number of variables	Advantages	Disadvantages
Fuzzy Logic	Low	Short/Long term	Multivariate	High accuracy in reflecting uncertainty qualitative knowledge; good at uncertain situation prediction of input variables.	Lack of specific prediction formulas; cannot reflect the relationship between predicted values and historical data; lacking self-learning capability and specific prediction formulas; requiring more pre-tuning and testing

Grey model	Low	Short/Medium-term	Univariate	Simple; high accuracy; the sample does not need regularity and large numbers; suitable for short- and medium-term prediction; fewer model parameters	Ignore the intrinsic mechanism of the system; cannot dynamically reflect system changes; can not consider the relationship between factors
Metaheuristic algorithms	High	Short/Long term	Multivariate	Conceptual simplicity; effective in processing a large amount of data and eliminating redundant information; able to solve a discrete optimizing problem; attractive for limited feature selection	Requiring change the problem presentation; high computational efforts; complex in learning and application; producing suboptimal solutions
Regression models	Low	Short term	Multivariate	Good at analyzing multi-factor models; provide error checking of model estimation parameters; easy to calculate; the correlation degree between the factors can be analyzed	Results cannot reflect periodic wave; poor generalization; low accuracy
Simulation model	Low	Short/Long term	Multivariate	Forecast under uncertainty; able to answer many questions; low data requirements to model; easy what-if scenario analysis; low cost; innovative approach	Good theories needed; no standardized approach; challenging to validate; potential scope creep in projects; high skepticism; political implications
Time series model	Low	Short/Long term	Univariate	The mathematical model requires only endogenous variables; popular and easy to adapt in a stationary time series with no missing sample	Require timing data to be stable; cannot reflect nonlinear relationships; the determination of model parameters is complicated
Machine Learning	High	Short term	Multivariate	Creating an optimal separating hyperplane in higher dimensional feature space; improving generalization performance and existing global minimum; automates forecast updates based on the recent data Increases adaptability to changes	Difficult to determine kernel function and separate real data perfectly; sensitive to missing data; high requirement in selecting hyperparameters; poor performance in multiple classification problem; maintenance complexity is high; technology requirements are high; the amount of required data is high
Neural Network	High	Short/Long term	Multivariate	Provide self-learning function and high-speed search for optimal solutions; fully approximate any arbitrarily complex nonlinear relationship; can learn and adapt to unknown or uncertain systems; highly robust; fully tolerant	No ability to explain reasoning process and reasoning basis; cannot work when data is insufficient; turning all reasoning into numerical calculations results in the loss of information; learning time is too long; large sample size required for model training

4.5. Conclusion and policy implications

The number of articles in demand forecasting increased significantly from 2008 due to the global financial crisis and the resulting severe consequences in both countries and companies all around the world especially in the energy SC market (see Fig. 4.4). Hence, this study presented a comprehensive review of demand forecasting of energy SC in the literature published between 2000 and 2020. From the application of our methodology, we selected a total of 267 articles that are further classified. We explored several issues like the number of publications, country/area, document types, energy types, research, and application areas. Moreover, we discovered about 73 different methods of energy demand forecasting which employed by authors in the last two decades (see Appendix Table 4.A1). Consequently, among these methods, there were eight methods with the most citations which encompass 56% of total publications. Traditional predicting approaches can be greatly manual and prone to individual bias. Thus, one of the aims of this study was to investigate the impact of Industry 4.0 in energy demand forecasting. Based on our literature review, we categorized these methods to Traditional (e.g. Fuzzy Logic, Grey model, Metaheuristic algorithms, Regression models, Simulation model, Time series model) and Intelligent (e.g. Machine Learning and Neural Network) models. After that, we concisely explained each method, investigated the most cited related articles in detail, and presented a complete list with different topics such as author(s) name(s), year, objective, energy types, citations, method used, application areas (see Tables 4.1–4.8). Since 2015, the number of research studies that employed intelligent methods for energy demand forecasting increased sharply in the literature. Therefore, we further considered the two most used intelligent methods of energy demand forecasting including Machine Learning (ML) techniques and Neural Networks (NNs) to review the most cited related investigations.

The actual boost from intelligent prediction methods happens when it is linked with human brainpower. Machines don't make mistakes, and people estimate and interpret the machine's results into decisions and activities. It is this symbiotic connection that results in successful intelligent predictions—particularly once individuals implement their results within the business (Hogan & Merrill, 2019). Concerning the Mckinsey report, errors were reduced by 30–50% in SC systems by employing intelligent forecasting methods. Moreover, if warehousing costs and inventory out-of-stock states decline about 10–40%, the enhanced precision leads to up to 65% decrease in lost sales. The projected influence of AI in SC is between \$1.2 T and \$2T in industrial and SC planning (McKinsey, 2017). Conversely, this outlook becomes real evidence as shown by Deloitte's analysis. A surprising 83% of the first companies that accepted AI has previously reached moderate (53%) or substantial (30%) monetary profits from their AI investments (Davenport & Schatsky, 2017). These earnings are only set to advance with time. Accenture's report presented that AI and intelligent forecasting will increase profitability by 38% and produce extra incomes to the tune of \$14 trillion by 2035 (Purdy & Daugherty, 2017).

Regarding Table 4.9, intelligent forecasting methods require a high level of data while this requirement is low in most traditional methods (except metaheuristic algorithms). In terms of "forecast period", both traditional and intelligent forecasting methods could cover short to long-term periods. In addition, in terms of the number of variables, both groups are multivariate. Moreover, in this table, the advantages and disadvantages of traditional and intelligent methods are explained completely.

Regarding Fig. 4.11, the trend for the number of research studies that employed intelligent methods for energy demand forecasting increased sharply starting in year 2015, while there was a fluctuation trend for traditional methods. Furthermore, in terms of the usage percentage of the forecasting methods from 2000 to 2020, traditional forecasting methods are prominent with 64% whereas intelligent methods have only 36% out of the total number of research studies. In terms of energy types from 2000 to 2020, the number of research studies which employed traditional methods were higher than intelligent methods especially in coal, oil and electricity, while in gas they were the same (see Fig. 4.12). Although Traditional methods were employed more, considering the trend that is mentioned Fig. 4.11, it is expected that the number of research studies which employ intelligent forecasting methods will increase. In terms of application areas from 2000 to 2020, intelligent methods are dominant to forecasting energy demand in Building, Data centers (DCs), Decentralized energy system, Demand side management, Hotels and Smart grid (see Fig. 4.13). The interesting point is that the forecasting of "National energy demand" is the most cited area for both methods (with 42 research studies for traditional and 18 for intelligent methods). As the authors mentioned in Section 4.2.2, China, USA, and Iran are the top three countries with the most publications in energy demand forecasting (see Fig. 4.7). It is indicated that about the forecasting of "National energy demand", both suppliers and buyers of energy in the world are concerned about the outlook of energy markets.

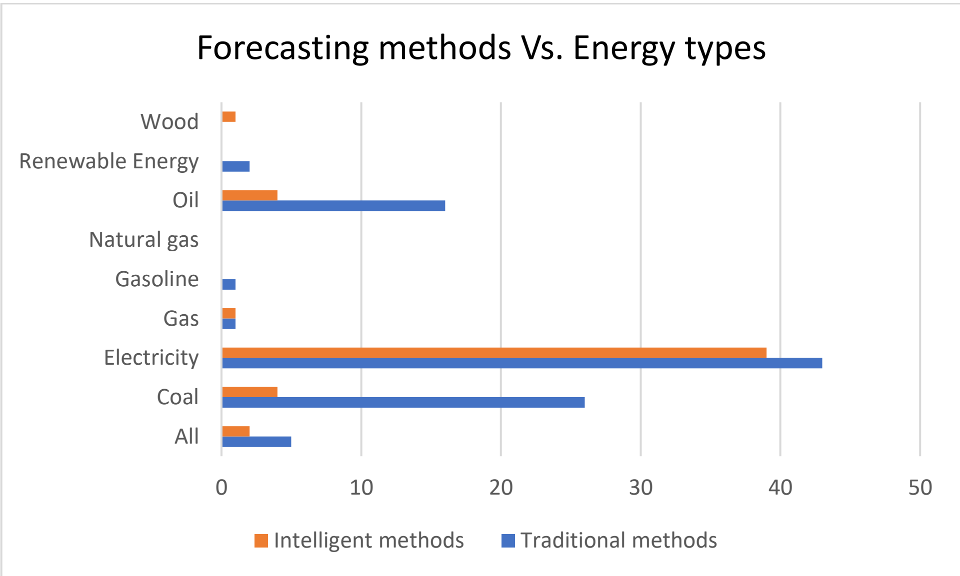

Fig. 4.12 The using of forecasting methods for different energy types

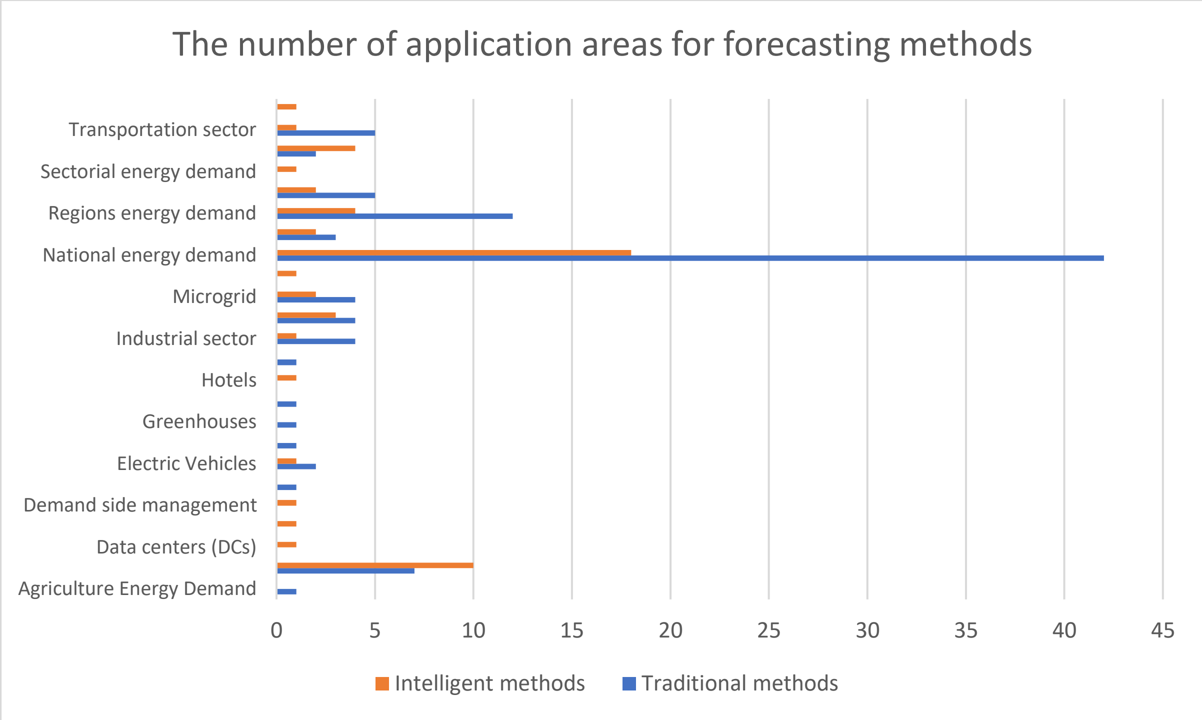

Fig. 4.13 The number of application areas for both Intelligent and Traditional forecasting methods

In addition to the above-mentioned issues, this study has some limitations. The following topics sum up these possible boundaries:

- This review is created for the exploration of Thomson Reuter's Web of Science. Other databases could be investigated as well.
- This review employed definite keywords to explore the database. Since the examination is greatly sensitive to these keywords, analyses that deviate slightly from these terms may have been ignored.
- Categorized research in this study are prepared generally on outcomes from academic journals (consider Fig. 4.6). Including more industrial reports in future work can advance this review's results.
- Moreover, the authors propose the following suggestions/speculations be enriched by future research:
- This study explains the most employed forecasting methods in the literature, including traditional and intelligent methods. Researchers could consider different forecasting methods of energy demand or dissimilar categories. For example, considering the rarely used methods or not-used methods.
- A new topic of future research is the development of hybrid approaches, especially a combination of Traditional and Intelligent forecasting methods.
- This study considered demand forecasting off all types of energy in the literature. Focusing on a specific type of energy such as renewable energy could be employed as well.
- Lastly, the resulting categorization tables are immensely helpful for determining prospects for more investigation in both Traditional and Intelligent forecasting models.

Paper Appendix-Chapter 4

Table 4.A-1. List of different methods of energy demand forecasting which employed by authors in last two decades

Methods/Year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
3D city model												1									
ADL-MIDAS model																			1		
Algebraic model																	1				
ANFIS Model																		1			
Artificial Intelligence (AI)																			1		
Bayesian approach															1	1		1		1	
BCVTB (Building Control Virtual Test Bed)														1							
Bottom up approach																1	1				
Central moving average (CMA)																1					
City Energy Analyst (CEA)																		1			
Clustering approach													1						1		
Cointegration Analysis and Artificial Intelligence Algorithm																			1		
Complete decomposition method		1																			
Computer Vision																				1	
Conjoint Analysis												1									
Convective heat transfer coefficients (CHTC)																				1	
Cycle analysis			1																		
Data Mining techniques															1						
Data-Driven Technique																			3		
Decision tree																					2
Demand response (DR)																	1				1
Dynamic input-output model																1					
Econometrics model				1					1								1	1		2	
EMD-GPM model																1					
Empirical Analysis													1								

End-use model																		1			
Energy demand of transport (EDT) model														1							
Exponential smoothing				1														1		1	
Extended input–output model														1							
Future Energy Management System (FEMS)														1							
Fuzzy Logic											1	1	1	1		1	1	1	3		1
General Circulation Model (GCM)																1					
Generalized additive models (GAM)																	1				
Generalized Logit model							1														
Grey model (GM)										1	2	4	3			1	2	3	2	2	1
Holt method									1												
K-Nearest Neighbor Approach															1						
LEAP											1	1			1	2		1		1	
Load and mobility data																			1		
Long Short Term Memory architecture																				1	
Machine Learning																1		3	3	4	
Markov chain												1							1		
Mathematical method												1								1	
Metaheuristic algorithm									1		2		7	2	1	2	4	2	1	1	
M-Pred																	1				
Multi-agent system model														1							
Neural Network (NN)		1	1			2	1	2	4	2	3	3		1	3	1	3	7	4	4	1
New urban energy demand forecasting system														1							
Nonparametric learning algorithm																1					
On-demand branch prediction (ODBP)																					1
Operational battery dispatch control algorithm															1						
Photovoltaic (PV) forecasting																	1		2		
Power Demand Probabilistic Forecasting														1							
Random Forest Regressor																				1	
Regression models									1	3			1	3				2		1	

Scenario analysis									1				1				1	2		1	
Simple model															1				1		
Simulation model														1	2		1	3	1	2	
Spatial dynamic panel model														1							
Stat-fusion											1										
Static load forecasting																				1	
Static method											1	1						1			
Stochastic forecast																1				1	
SunDial System																			1		
Surrogate model																				1	
Survey									1												
System Dynamics																				1	
Thermodynamic analysis					1																
Time series model					1		1	1	1			1	1		3	1	3	1	3	2	
Transport workload method													1								
Travel demand model																		1			
Two-step approach																			1		
Weather Research and Forecast (WRF)														1			1	1			
WinWatt, PHPP																		1			

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Integrate exergy costs and carbon reduction policy in order to optimize the sustainability development of coal supply chains in uncertain conditions

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ABSTRACT

The coal supply chain in developing countries is supposed to have the lowest cost overall; however, in terms of sustainability (social, economic, and environmental aspects) and considering Joules rather than monetary objectives, does this assumption remain accurate? This research develops a sustainable model for coal supply chain in five countries by integrating exergy costs and carbon tax policy using the extended exergy accounting (EEA) method under an uncertain environment. This sustainable model is a single vendor multi-buyer economic order quantity (EOQ) model for coal supply chain with the objective of the least total exergy with the maximum carbon and imperfect quality items decrease. Additionally, some realistic suppositions such as waste disposal to the environment, the obtainable budget of buyers and stockout in the model are considered. Following this, four metaheuristic algorithms, such as WOA, GA, ACO, and SA, are suggested to solve the model, and their results are validated by the exact method (GAMS). Finally, to improve the model's sustainability, a sensitivity analysis with different exergy values is offered for coal supply chain in each country. According to the results, coal supply chains in Canada and Germany have better sustainability performance (in Joules) than Iran and Turkey.

1. Introduction

Nowadays, the energy market is maturing and unstable, characterized by intensifying demand and fluctuating supply (Roozbeh Nia et al., 2021). Additionally, harmful ecological circumstances and competitive situations are converting stricter, whereas the decline of natural fuel resources impacts energy management (Caglayan and Caliskan 2021). Undeniably, inappropriate energy utilization significantly impacts and damages the environment (Roozbeh Nia et al., 2021). It is reported that the annual consumption of energy in the Organization for Economic Co-operation and Development (OECD) countries have risen by 0.5%. In comparison, this amount for non-OECD countries has expanded by about 1%. Moreover, from 2006 to 2030, energy utilization in the industrial section (non-OECD and OECD countries) grew by about 1.4% per annum (U.S. Energy Information, 2020). The energy supply is a vital element of industrial developments that broadly influences ecosystems, degrades them, and produces environmental greenhouse gases. Consequently, reducing energy utilization is crucial for environmental protection and developing sustainable resources (Jawad and JaberNuwayhid, 2018).

As a key fundamental energy source, coal has a critical position in stabilizing national economies (Kang et al., 2014). Coal is the world's greatest sole source of electrical energy (37%) and will continue the most significant supplier (22%) until 2040. Coal aids non-energies manufacturing such as cement, steel (70%), and aluminium production (60%), rare earth element extraction, coal-to-chemicals, carbon fibre manufacture, and industrial electrodes (World coal association). Typically, about 630 kg of coal are demanded to produce one metric ton of steel (Corsa). To produce one tonne of cement, approximately 200–450 kg of coal is required and about 20% of hydrogen production occurs by coal-to-gas processes (World coal association). Concerning providing renewable energy, for instance, each wind turbine needs 260 tonnes of steel created from 170 tonnes of coking coal. In Appendix Fig. A.1, global coal consumption by region in 2021 is presented (Statistical, 2021). Coking coal, also named metallurgical coal, is a type of non-renewable resource, and it is mainly intended for coke making. For sustainable development, coal resources must be used scientifically and rationally (Zhang et al., 2021a). Steel manufacturers worldwide have a considerable demand for coking coals because it is one of the essential unique inputs for steel production employing blast furnaces (Mohanty

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CHAPTER 5. PAPER THREE - INTEGRATE EXERGY COSTS AND CARBON REDUCTION POLICY IN ORDER TO OPTIMIZE THE SUSTAINABILITY DEVELOPMENT OF COAL SUPPLY CHAINS IN UNCERTAIN CONDITIONS

Forewords

After literature reviewing in Chapters 3 and 4, this chapter aims to improve the sustainability of coal SC in both developed and developing countries by incorporating extended exergy accounting and carbon tax policy. Moreover, carbon policies such as trade, cap and offset will be covered in Chapters 6, 7 and 8, respectively.

Abstract

The coal supply chain in developing countries is supposed to have the lowest cost overall; however, in terms of sustainability (social, economic, and environmental aspects) and considering Joules rather than monetary objectives, does this assumption remain accurate? This research develops a sustainable model for coal supply chain in five countries by integrating exergy costs and carbon tax policy using the extended exergy accounting (EEA) method under an uncertain environment. This sustainable model is a single vendor multi-buyer economic order quantity (EOQ) model for coal supply chain with the objective of the least total exergy with the maximum carbon and imperfect quality items decrease. Additionally, some realistic suppositions such as waste disposal to the environment, the obtainable budget of buyers and stockout in the model are considered. Following this, four metaheuristic algorithms, such as WOA, GA, ACO, and SA, are suggested to solve the model, and their results are validated by the exact method (GAMS). Finally, to improve the model's sustainability, a sensitivity analysis with different exergy values is offered for coal supply chain in each country. According to the results, coal supply chains in Canada and Germany have better sustainability performance (in Joules) than Iran and Turkey.

Keywords Carbon tax policy; Extended exergy accounting (EEA); Coal supply chain

Sustainability; Metaheuristic algorithm; Fuzzy EOQ

5.1. Introduction

Nowadays, the energy market is maturing and unstable, characterized by intensifying demand and fluctuating supply (Roozbeh Nia et al., 2021). Additionally, harmful ecological circumstances and competitive situations are converting stricter, whereas the decline of natural fuel resources impacts energy management (Caglayan and Caliskan 2021). Undeniably, inappropriate energy utilization significantly impacts and damages the environment (Roozbeh Nia et al., 2021). It is reported that the annual consumption of energy in the Organization for Economic Co-operation and Development (OECD) countries has risen by 0.5%. In comparison, this amount for non-OECD countries has expanded by about 1%. Moreover, from 2006 to 2030, energy utilization in the industrial section (non-OECD and OECD countries) grew by about 1.4% per annum (U.S. Energy Information, 2020). The energy supply is a vital element of industrial developments that broadly influences ecosystems, degrades them, and produces environmental greenhouse gases. Consequently, reducing energy utilization is crucial for environmental protection and developing sustainable resources (Jawad and JaberNuwayhid, 2018).

As a key fundamental energy source, coal has a critical position in stabilizing national economies (Kang et al., 2014). Coal is the world's greatest sole source of electrical energy (37%) and will continue the most significant supplier (22%) until 2040. Coal aids non-energies manufacturing such as cement, steel (70%), and aluminum production (60%), rare earth element extraction, coal-to-chemicals, carbon fiber manufacture, and industrial electrodes (World coal association). Typically, about 630 kg of coal are demanded to produce one metric ton of steel (Corsa). To produce one ton of cement, approximately 200–450 kg of coal is required and about 20% of hydrogen production occurs by coal-to-gas processes (World coal association). Concerning providing renewable energy, for instance, each wind turbine needs 260 tons of steel created from 170 tons of coking coal. In Appendix Fig. 5.A.1, global coal consumption by region in 2021 is presented (Statistical, 2021). Coking coal, also named metallurgical coal, is a type of non-renewable resource, and it is mainly intended for coke making. For sustainable development, coal resources must be used scientifically and rationally (Zhang et al., 2021a). Steel manufacturers worldwide have a considerable demand for coking coals because it is one of the essential unique inputs for steel production employing blast furnaces (Mohanty et al., 2019). For instance, in 2019, the coal utilization in the steel sector was around 900 million tons of coal equivalent (Mtce) (26.2 EJ [EJ]) or about 15% of the initial international coal demand (Iron and Steel Technology Roadmap).

With the rapid growth in environmental protection, companies inside a coal supply chain, such as steel companies, are keenly seeking novel approaches beneficial for green manufacturing (Yin et al., 2020). Coal's primary gas emissions, such as CO2, SO2, NOX, and smoke dust, can contribute to global warming, damaging the ozone layer and creating acid rain (Manisalidis et al., 2020). Both coal burning and mining leave overburdened pollution in water and air resources. Hence, researching the ecological consequences of coal production and consumption is a prominent topic (Mann and Spath, 2001). In this topic, researchers agree that pricing emissions of carbon are the low-cost and most effective method for improving the sustainability of supply chain (Environment and Climate Change Canada, 2018). The significant policies for carbon pricing in the literature are carbon tax, carbon cap, carbon trade, and carbon offset (Malladi and Sowlati, 2020). Regarding sustainability and economic issues, the outputs of carbon policies in supply chain are unequal.

Supply chains are the operational sequence of interconnected procedures that manage, plan, and control goods and services between buyers and vendors (Roozbeh Nia et al., 2020). Besides the monetary costs of a coal supply chain, for instance, miners, washing factories, shippers, and power plants/steel producers, there are other charges known as "hidden costs" associated with environmental influences and emissions. Both costs should be considered in the entire operational costs of the coal supply chain (Phillips, 2008). Any manufacturing process that reduces "hidden costs," for instance, environmental effects, is recognized as a sustainable procedure. To a greater extent, sustainability in the supply chain of coal is complicated because it faces further consequences, for instance, social and ethical hazards (Naderi et al., 2021a). An example of Iranian coal supply chain with 4-item and five buyers are presented in Fig. 5.1.

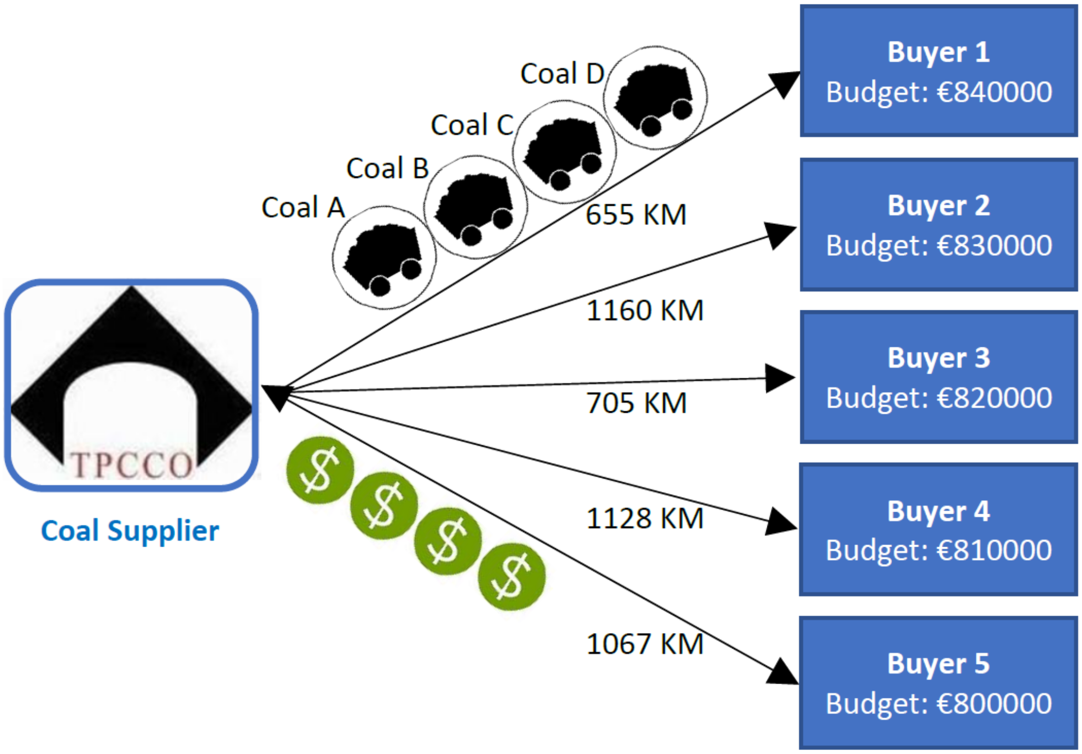

Fig.5.1. An example of Iranian coal SC with 4-item and five buyers (with distance and available budgets)

Growing pressure from external shareholders to sustain company processes has fostered businesses to focus on their environmental effects and promise to implement sustainability measures in the future (Qu et al., 2019; Liu et al., 2021). Sustainable supply chain management considers social, environmental, and financial costs locally, nationally, and worldwide (Asadi and Sadjadi, 2017; Bui et al., 2020; Mangla et al., 2017). More precisely, sustainable supply chain management must be expressed to fulfill the necessities of the existing generation of businesses without failing the capability of forthcoming generations (for example, Industry 4.0) to accomplish their needs (Jabbour et al., 2020). The specialists in the multi-tier manufacturing supply chain have recognized that managing the first-tier suppliers' sustainability is insufficient to reach a sustainable performance in the whole supply chain (Sharma et al., 2021). It needs careful consideration by all practitioners in a supply chain. The integration of three sustainability aspects, for instance, economic, ecological, and social factors of a system, can be reached by applying exergy analysis (Jawad and JaberNuwayhid, 2018; Dincer and Rosen, 2012). An innovative approach that can support a supply chain to be more sustainable is Extended Exergy Accounting (EEA) (Aghbashlo et al., 2018). This method integrates the effect of non-energetic manufacturing features into the complete loss assessment (Jawad and JaberNuwayhid, 2018; Sciubba, 2011). The primary benefit of employing the EEA method in the production system is that this method states all outcomes in Joules (instead of dollars); therefore, acceptable assessments among various products can be achieved (Naderi et al., 2021b; Jawad and JaberNuwayhid, 2018).

The functioning of the entire coal supply chain is one of the critical interests of the concerned participants (Mehmood et al., 2015). As society increasingly recognizes the value of the environment, waste disposal and carbon emission must become two of the leading indicators of coal supply chain assessment. Additionally, employing different carbon pricing strategies result in various costs and carbon reductions in supply chain. Moreover, as we will see in the literature review section, the number of publications employing the EEA method is insufficient. Additionally, to the best of the authors' knowledge, no study considers carbon reduction policies with the EEA method (or exergy analysis) at the same time in a coal supply chain. Therefore, we can present three main research questions as follows.

Q1. Does incorporating a carbon reduction strategy with the EEA method in coal supply chain trigger financial benefits and sustainability advantages?

Q2. The coal supply chain in developing countries is supposed to have the lowest cost overall; however, in terms of sustainability (social, economic, and environmental aspects) and considering Joules rather than monetary objectives, does this assumption remain accurate?

Q3. Which percentage set of exergy components (social, economic, and environmental characteristics) creates the lowest total exergy of supply chain? which country has more sustainable conditions for coal supply chain?

5.2. Literature review

In view of the fact that in the literature, no publication considers the EEA method (or exergy analysis) simultaneously with carbon reduction policies in coal supply chain, in this section, we focus on recent publications related to exergy analysis and the EEA method.

5.2.1. Exergy analysis

Discovering a similarity between the thermal and production procedure is a new idea that inspired some researchers to merge the notions of the first and second laws of thermodynamics with the inventory model (Jawad et al., 2015). Exergy analysis can facilitate finding an organization's wastefulness (Koroneos and Tsarouhis, 2012). It has been broadly exploited through various manufacturing and industrial companies, for example, food (Apaiah et al., 2006), aluminum (Balomenos et al., 2011), cement (Madlool et al., 2012), recycling of metal (Amini et al., 2007), management of waste (Gaudreau et al., 2009), and manufacturing (Gutowski et al., 2009). The name "exergy" was initially suggested by Rant (1956), even though other investigators had previously outlined similar meanings. Some academics like Jaber et al. (2004, 2006, 2009), Jaber and Rosen (2008), Apaiah et al. (2006), and Geldermann et al. (2006) have employed entropy methods, exergy analysis and information theory to explain chaos when modeling the performance of productive systems/processes. Moreover, employing exergy analysis in a simple economic order quantity (EOQ) model was done by Jaber et al. (2011) and Santhi and Karthikeyan (2015), respectively. Additionally, Jaber and Jawad (2015) used the second law of thermodynamics to estimate the entropy created in economic production quantity (EPQ) and Just-in-Time (JIT) systems. To calculate the costs of disorder (entropic), the authors incorporated an entropic part to the cost functions of the model. The outcomes revealed that a JIT strategy is more costly than an EPQ policy.

Furthermore, Jaber et al., (2017) established the conventional models of the economical manufacture quantity (EMQ) and JIT by covering other topics like transportation, defective products, work associated with stress/fatigue, pollution costs, and greenhouse gases (GHG) from transport and manufacture systems. They suggested that JIT experiences lowered costs than the EMQ model when correlated stress and entropy costs were not calculated. Afterward, Jawad et al. (2018) examined the most prominent issues that can affect the entire cost of a supply chain, for instance, emissions, labor, energy (from manufacture and shipping), social effects of shipping, and entropy. The authors accepted that a two-stage supply chain (producer-buyer) is comparable to a thermal system of two heat pumps connected in sequence. They established an exergy cost function (mega-joules; MJ per year) and optimized utilized exergy as a part of sustainable development with two approaches: conventional (Hill's) and the consignment stock methods. They showed that optimizing the exergy cost function escalates the money to society for a slight extra rise in cost on the supply chain. Naderi et al. (2021a) offered a mathematical model for increasing sustainability concerning the cost of exergy demolition (entropy) for a coal supply chain in Iran. The authors applied exergy analysis for a model that involves economic and wasted exergy costs. Their results indicated that the suggested method delivers saving in the consumed exergy by allowing an additional financial cost.

5.2.2. EEA method

Regarding the EEA method, to the best of the authors' knowledge, few studies employed this method for inventory management or supply chain. The method of EEA introduced by Sciubba (2001) includes energy and raw material with other non-energetic manufacturing aspects like the costs of financial, labor, and environmental remediation. For example, Dai et al. (2012) employed the EEA method to investigate a group of social-economic utilization systems in China and explain the connection among different divisions through a thermodynamic metric. Moreover, Jawad et al. (2015) estimated the exergy costs using the EEA method under the EOQ inventory model. They used an exergetic model to find the order quantities for companies in Germany, the USA, and China. The outcomes presented that the order quantity is not equal for the three companies since the corresponding exergy of financial, labor, and environmental remediation expenses are not similar in each country. Later, Jawad et al. (2016) reviewed the economic production quantity (EPQ) model to indicate sustainability requirements. They applied the laws of thermodynamics, combined with the EEA method, to determine the sustainability of a production-inventory system and realized that sustainability could be beneficial in some circumstances. Recently, Naderi et al. (2021b) provided an analysis of exergy to develop and evaluate the utilized exergy designed for a sustainable food supply chain. Their model concerns with divergent economic, environmental, and social functions in choosing the further sustainable supply chain to make and deliver items. They employed a hybrid metaheuristic algorithm on simulated annealing (SA) and GA to solve the model.

To learn more about exergy and the EEA method, concerned scholars may suggest Ehyaei et al. (2019), Arango-Miranda et al. (2018), and Dincer and Rosen (2012). In addition, a review of research works of exergy analysis and the EEA method, along with our proposed model, is offered in Table 5.1. Traditional inventory models do not reflect inventory systems' unseen (indirect) costs. In fact, in earlier research, the cost meaning is workflow-associated cost aspects. It is limited to finding a study that evaluates the supply chain in terms of Joules (rather than conventional monetary objectives) and simultaneously assesses all sustainability features, for example, economic, labour, and environmental. There is an absence of analysis to find the best percentage of exergy components (social, economic, environmental aspects) in the EEA method for a supply chain. Additionally, to the best of the authors' knowledge, no exergy analysis approach like the EEA in the literature consider carbon tax strategy in supply chain. Moreover, there is an absence of studies that evaluate the sustainability of coal supply chains in developed and developing countries with carbon tax strategy in terms of Joules. Lastly, there is a lack of research in the literature that evaluates the supply chain under a carbon tax strategy with vague parameters such as buyer demand.

Hence, to improve sustainability, this study considers all three hidden costs (labor, money, and ecological remediation costs) using the EEA technique integrated with carbon reduction policy (carbon tax) for a coal supply chain in Iran while utilizing Joules as a universal unit of measure (rather than monetary values). In terms of modeling, this research considers the studies of Jawad et al. (2015) and Naderi et al. (2021a) and, more precisely, develops it to a multi-item multi-constraint multi-buyer EOQ model in coal supply chain in Iran under uncertainty condition. This supply chain has a single vendor and multi-buyer (SVMB) that coordinate with the VMI approach and considers inventory stockout as a backorder. Additionally, a penalty cost for imperfect quality items disposal to the environment is considered to make the model green. Four metaheuristic algorithms, including GA, ACO, SA, and the whale optimization algorithm (WOA), are suggested to acquire a near-optimum solution of the developed exergy fuzzy nonlinear integer programming (EFNIP). In our models, we consider different objectives simultaneously, such as the costs of the inventory system, an additional budget of each buyer, the cost of poor-quality items disposal to the environment, and carbon emission related to all processes of coal supply chain. Moreover, we employ the EEA method to convert the traditional monetary costs of our models to the exergetic values of coal supply chain (values in Mega-Joules; MJ) for capital, labor, and environment. We are looking to get the optimum value of three decision variables, such as the amount of required loan (more budget) for each buyer (B_j^-), order quantity of each item for each buyer (Q_{ij}), and amount of backorder of each item for each buyer (b_{ij}). A real case study in a coal supply chain in Iran and eight arbitrary numerical examples with various numbers of items were offered. After that, for validation of the results by all metaheuristic algorithms, they are compared with the exact model (GAMS). In the last part, a sensitivity analysis was done to reach a win-win financial and sustainability advantages situation for the coal enterprises with the lowest total exergy and carbon emission. It includes different percentages for exergy costs in coal supply chain of five countries: Iran, Afghanistan, Turkey, Germany, and Canada. Therefore, the main contributions of this research are as follows:

- Developing the sustainability of coal supply chains in terms of Joules under carbon tax strategy and the ambiguous environment by using the EEA method.
- Evaluating the sustainability of coal supply chains in five countries to find out which country has the most sustainable coal supply chain in terms of Joules.
- Obtaining the best value of exergy components for coal supply chain in five countries.

The rest of the manuscript is defined in this way. In Section 5.3, the problem is outlined, the suppositions are stated, and the model is mathematically expressed into a fuzzy nonlinear integer-programming model (non-exergy model) under two carbon emission policies. In Section 5.4, the non-exergy models are converted to the exergy equivalents using the EEA method. The suggested metaheuristic algorithms are presented in Section 5.5 to solve the problem. To reveal the relevance of the proposed solution method, computational test problems and sensitivity analysis of exergy values for five countries are recommended in Section 5.6. Conclusions and forthcoming studies are offered in Section 5.7.

Table 5.1. A review of research works in exergy analysis of supply chain

Authors	Objective	Single objective /multi	Solving Methods	Validation	Compare SCs	Inventory model	EEA method	Emission policy	Over-budgeting	Uncertainty	Shortage	VMI strategy	Waste disposal	Multi-buyer
Naderi et al. (2021a)	Provide a mathematical model for improving coal SC sustainability while minimizing the cost of exergy destruction (entropy) in SC	Single	Metaheuristic algorithm	No	No	No	No	No	No	No	No	No	No	Yes
Naderi et al. (2021b)	Provide an exergy analysis to model and minimize the consumed exergy for sustainable SC	Single	Metaheuristic algorithm	Branch & bound	No	No	Yes	No	No	No	No	No	No	Yes
Jawad et al. (2018)	Minimize the total cost of the developed SC model while focusing on the pillars of sustainable developments.	Single	Exact method	N/A	No	Yes	No	No	No	No	No	No	No	No
Banasik et al. (2017a)	Develop a mathematical model for quantitative assessment of alternative production options that are associated with different ways to deal with waste in food SCs	Multi	Exact method	N/A	No	No	No	No	No	No	No	No	Yes	No
Banasik et al. (2017b)	Quantify trade-offs between economic and environmental indicators and explore quantitatively alternative recycling technologies	Multi	Exact method	N/A	No	No	No	No	No	No	No	No	No	Yes
Jawad et al. (2016)	Re-examines the economic production quantity (EPQ) model to reflect the needs of sustainability by using EEA and the laws of thermodynamics.	Single	Exact method (EPQ formula)	N/A	N/A	Yes	Yes	No	No	No	No	No	No	No
Jawad et al. (2015)	Use an exergy model to determine the EOQ inventory policies for three firms operating in the USA, Germany, and China.	Single	Exact method (EOQ formula)	N/A	N/A	Yes	Yes	No	No	No	No	No	No	No

Santhi and Karthikeyan (2015)	Determine the cycle length and the replenishment order quantity of an EOQ model to maximize the profit.	Single	Exact method (EOQ formula)	N/A	N/A	Yes	No	No	No	Yes	No	No	No	No
Jaber et al. (2009)	A mathematical model to determine batch sizes for deteriorating items while minimizing the entropy of the EOQ model.	Single	Exact method (EOQ formula)	N/A	N/A	Yes	No	No	No	No	No	No	No	No
Jaber and Rosen (2008)	Improve production system performance by applying thermodynamics' first and second laws to reduce system entropy (or disorder).	Single	Exact method (EOQ formula)	N/A	No	Yes	No	No	No	No	No	No	No	No
Jaber (2007)	Estimate the hidden costs of the EOQ model by applying the first and second laws of thermodynamics to reduce system entropy (or disorder) at a cost.	Single	Exact method (EOQ formula)	N/A	N/A	Yes	No	No	No	No	No	No	No	No
Proposed model	Optimize the sustainability of coal SC in five countries with the integration of the EEA method and carbon tax policy	Single	Metaheuristic algorithm	GAMS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

5.3. Problem explanation and model formulation

5.3.1. Problem description

The warehouse is vital for every company because it is a safe place for their stock. Although inventory is one of the most significant precious possessions, managing it generates a load of defective quality materials and carbon emission, which is discarded into the environment. Moving on the green with implementing sustainable inventory management methods will benefit both the environment and the enterprise. In other words, adding sustainability to the inventory management of a supply chain leads to a decrease in both the social and ecological consequences of a business with no critical impact on profitability. Based on Section 2, this study is focused on an SVMB coal supply chain in Iran with multiple items and poor-quality operating under the EOQ model. The objective function is optimizing the total exergy of coal supply chain (in terms of Joules instead of money) by incorporating the EEA method and different carbon emission policies. To bring this sustainable exergy model to real-world problems, we consider some realistic assumptions such as waste (imperfect quality items) disposal to the environment, uncertainty in buyer's demand, vendor's sales capacity, vendor managed inventory (VMI) contract between supplier and buyers. Moreover, the constraints include the storage space, the over-budgeting of each buyer, the boundary on the orders of all buyers, the total number of orders, and the vendor's sales capacity.

5.3.2. Assumptions

Regarding the purpose of this study to improve the sustainability of coal supply chain by integrating carbon policies and the EEA method, we consider the succeeding suppositions for the mathematical preparation. More sophisticated assumptions are considered for future research in Section 7.

(a) A coal supply chain includes a single vendor (supplier), multi-buyer (steel companies) by n items (different grades of coal)

(b) EOQ model is considered for the inventory model of coal supply chain (production rate is infinite).

(c) lead time for purchased items is presumed zero.

(d) Inventory stockout is permitted (as a backorder) for all items, while the linear backorder cost per unit per time unit is recognized for all items, and the time-independent fixed backorder cost per unit is presumed zero for all items.

(e) The price for the entire item is stable in the scheduling cycle

(f) Discount by quantity is not permitted

(g) The vendor pays the transportation cost

(h) Buyer's demand for all items is indistinct (triangular fuzzy number)

(i) The ordering and holding costs, as well as emission tax, are known

(j) The buyer's storage space capacity is limited

(k) The total available budget of each buyer is limited, but the over-budgeting is permitted with some additional costs

(l) The vendor's sales capacity of all items is restricted, but it is indistinct (triangular fuzzy number)

(m) The number of all orders by all buyers is limited

(n) The buyer's order amount of an item is restricted (a lower and a higher limit due to transportation capacity)

(o) All processes in coal supply chain include mining (vendor), transportation, and using coal in the steel company (buyers), producing carbon emission and waste (imperfect quality items) disposal to the environment

(p) Distance between vendor and all buyers is fixed and known. The railway system does the transportation of all orders.

5.3.3. Notations

The symbols, parameters and decision variables of the supply chain model are presented as follows.

5.3.3.1. Parameters

i: Index of items (coal); $(i = 1,2, \dots, n)$

j: Index of buyers; $(j = 1,2, \dots, m)$

D_{ij}: Demand rate of coal i for buyer j

V_i: Lower limit of transportation capacity on the order amount of item i

W_i: Upper limit of transportation capacity on the order amount of item i

G: Maximum sales capacity of the vendor on the total order amount of all items

N: Maximum total number of orders by all buyers

C_i: Purchasing price per unit of item i

C_{tax}: Emission tax of each unit of carbon produced by different supply chain processes

C_{waste}: Cost of waste (imperfect quality items) produced by different supply chain processes

B_j: Total available budget of all items for buyer j

int^{-}: The interest rate of the required loan for buyer j

$A_{i,s}$: Vendor's stable ordering cost per unit of item i

$A_{ij,t}$: Stable shipping cost per unit of item i for buyer j, which is paid by the vendor (VMI contract)

$A_{ij,b}$: Stable ordering cost per unit of item i for buyer j

h_{ij}: Stock keeping cost per unit of item i at the warehouse of buyer j in a period

s_1: The cost of backordering a unit for one year (time-independent)

s_2: Linear backorder cost per unit per time unit

F_j: Available storage capacity of buyer j for all items

L_j: Distance between vendor and buyer j (km)

f_m: Emissions factor of mining (ton/unit)

f_t: Emissions factor of transportation (ton/unit)

f_k: Emissions factor of furnace in steel manufacturer (ton/unit)

α: Proportion of imperfect quality items in the mining process

β: Proportion of poor-quality items in the transportation process

γ: Proportion of defective quality items in steel manufacturer

5.3.3.2. Decision variables

Q_{ij}: Order quantity of item i for buyer j

b_{ij}: Backorder amount of coal i for buyer j in a cycle

B_j^-: Total required loan for buyer j

The following subsections will develop a non-exergy mathematical model of the coal supply chain for carbon tax policy (subsection 5.3.4). Then the model is converted to an exergy fuzzy model (subsection 5.3.5).

5.3.4. A non-exergy Modeling of coal supply chain with carbon tax policy

5.3.4.1. Objective function

In the model under carbon tax policy, four objectives are defined. First, the total inventory cost of coal supply chain (TC_1) includes the ordering (TO_{ij}), holding (TH_{ij}), backorder (TS_{ij}), purchasing (TP_{ij}), and transportation (TT_{ij}) costs (Syntetos, 2014; Pasandideh et al., 2010, 2011; Razmi et al., 2010) as

$$TC_1 = TO_{ij} + TH_{ij} + TS_{ij} + TP_{ij} + TT_{ij} \tag{5.1}$$

Where,

$$TO_{ij} = \sum_{i}^{n}\sum_{j}^{m}\frac{D_{ij}}{Q_{ij}}\left(A_{i,s} + A_{ij,b}\right) \tag{5.2}$$

$$TH_{ij} = \sum_{i}^{n}\sum_{j}^{m}\frac{h_{ij}}{2Q_{ij}}\left(Q_{ij}(1-\alpha) - b_{ij}\right)^2 \tag{5.3}$$

$$TS_{ij} = \sum_{i}^{n}\sum_{j}^{m}\left(\frac{s_1.b_{ij}^2}{2Q_{ij}} + \frac{s_2.b_{ij}.D_{ij}}{Q_{ij}}\right) \tag{5.4}$$

$$TP_{ij} = \sum_{i}^{n} \sum_{j}^{m} C_i D_{ij} \tag{5.5}$$

$$TT_{ij} = \sum_{i}^{n} \sum_{j}^{m} \frac{D_{ij}}{Q_{ij}} (A_{ij,t}) \tag{5.6}$$

Where (D_{ij}, Q_{ij}, h_{ij}) are the demand rate of coal *i* for buyer *j*, order quantity of item *i* for buyer *j* and holding cost per unit of coal *i* for buyer *j,* respectively. Second, the total cost associated with the additional required budget of all buyers. In our model, the over-achievement budget (B_j^-) is considered the cost. It means the buyer should get a loan (B_j^- as a decision variable) with an interest rate of (int^-). In this case, the buyer should pay this loan and the corresponding interest rate $(B_j^- + [int^- \times B_j^-])$ after the end of the year. Consequently, the whole cost related to the budget of all buyers (TC_2) is

$$TC_2 = \sum_{j}^{m} [B_j^- + (int^- \times B_j^-)] \tag{5.7}$$

Third, to make the model green, we consider that all coal supply chain processes produced some imperfect quality items such as coal refuse, coal waste, and coal tailings to be discarded into the environment. This waste has a total penalty cost as

$$TC_3 = C_{waste} \times \sum_{i}^{n} \sum_{j}^{m} [(Q_{ij}.\alpha) + (Q_{ij}.(1-\alpha).\beta) + (Q_{ij}(1-\alpha).(1-\beta).\gamma)] \tag{5.8}$$

Where (α, β, γ) are the proportions of imperfect quality items in mining, transportation, and steel manufacturer processes, respectively. Moreover, C_{waste} is the unit cost of imperfect quality items produced by different supply chain processes. The carbon tax strategy is a tax cost on carbon discharges (Wesseh and Lin, 2018). The government charges a carbon tax (C_{tax}) on each carbon unit produced by coal supply chain companies. Hence, the entire cost of a coal supply chain includes the emission cost, whereas there is an adjustment regulation between the process cost and the tax cost of emission there. It means coal companies should stabilize the process and the emission costs consistent with various carbon tax amounts to optimize the entire cost (Li et al. 2020). Hence, the fourth objective of the model is created as

$$TC_4 = C_{tax} \times \sum_{i}^{n} \sum_{j}^{m} \left[(Q_{ij}.f_m) + \left(\frac{D_{ij}}{Q_{ij}}.L_j.f_t \right) + (Q_{ij}.D_{ij}.f_k) \right] \tag{5.9}$$

Where (f_m, f_t, f_k) are emissions factors in mining, transportation, and steel manufacturer processes, respectively. Moreover, L_j is the distance between the coal vendor and buyer *j*. Eq. (5.9) is the summation of produced carbon in mining, transportation, and steelmaking processes. So, the combination of the above four objectives $(TC_{tax} = TC_1 + TC_2 + TC_3 + TC_4)$ makes the non-exergy total cost of coal supply chain under emission tax policy.

5.3.4.2. The limitations

As revealed earlier, a real-world VMI contract includes the vendor and all the buyers in the coal supply chain. This type of VMI contract accepting a limitation for the available budget of each buyer (B_j) and consider related costs for this issue as follows:

$$\sum_{j}^{m}\sum_{i}^{n} C_i . Q_{ij}(1-\alpha) \leq B_j + \left(B_j^-\right) \tag{5.10}$$

Where (C_i) is purchasing price per unit of item i. Eq. (10) demonstrates that if the total paid out money of a buyer is greater than the available budget ($\sum_i^n C_i . Q_{ij}(1-\alpha) > B_j$), then the buyer needs to get a loan with the amount of ($B_j^- > 0$). This amount (B_j^-) is not determined before since it is a decision variable in the model, and in Eq. (5.7), the total cost related to this constraint is formulated. Moreover, the storage capacity of each buyer (F_j) is constrained (Cárdenas-Barrón et al. 2012),

$$\sum_{j}^{m}\sum_{i}^{n}\left(Q_{ij}(1-\alpha) - b_{ij}\right) \leq F_j \tag{5.11}$$

Where (b_{ij}) is the backorder amount of coal i for buyer j in a cycle (a decision variable). Furthermore, the railway transportation system among the vendor and buyers has some limitations in capacity. So, the Min. (V_i) and Max. (W_i) of the transportation capacity for each order quantity (Q_{ij}) are

$$V_i \leq Q_{ij} \leq W_i \tag{5.12}$$

In addition, the vendor has a limitation for its total sales capacity (G), which is as follows:

$$\sum_{i}^{n}\sum_{j}^{m} Q_{ij} \leq G \tag{5.13}$$

Likewise, there is a constraint on the total number of orders (N) by all buyers:

$$\sum_{i}^{n}\sum_{j}^{m} \frac{D_{ij}}{Q_{ij}} \leq N \tag{5.14}$$

Lastly, the j^{th} buyer's highest amount of backorder of an item i in a cycle should be fewer than or equal to its lot size (Q_{ij}). Therefore

$$b_{ij} \leq Q_{ij} \tag{5.15}$$

It should be stated that for simplifying the mathematical model, we ignore the cost of purchasing (Eq. 5.5) since it does not affect order quantity (Q_{ij}) in the model. With regards to Eqs. (5.1)-(5.15), the model of "multi-item" SVMB EOQ with the VMI strategy under carbon tax policy can be easily obtained as

$$TC_{tax} = \sum_{i}^{n}\sum_{j}^{m}\left[\frac{D_{ij}}{Q_{ij}}\left(A_{i,s} + A_{ij,b}\right) + \frac{h_{ij}}{2Q_{ij}}\left(Q_{ij}(1-\alpha) - b_{ij}\right)^{2} + \left(\frac{s_1.b_{ij}^{2}}{2Q_{ij}} + \frac{s_2.b_{ij}.D_{ij}}{Q_{ij}}\right) + \frac{D_{ij}}{Q_{ij}}\left(A_{ij,t}\right)\right] + \sum_{j}^{m}\left[B_j^{-} + \left(int^{-} \times B_j^{-}\right)\right] + C_{waste} \times \sum_{i}^{n}\sum_{j}^{m}\left[\left(Q_{ij}.\alpha\right) + \left(Q_{ij}.(1-\alpha).\beta\right) + \left(Q_{ij}(1-\alpha).(1-\beta).\gamma\right)\right] + C_{tax} \times \sum_{i}^{n}\sum_{j}^{m}\left[\left(Q_{ij}.f_m\right) + \left(\frac{D_{ij}}{Q_{ij}}.L_j.f_t\right) + \left(Q_{ij}.D_{ij}.f_k\right)\right]$$

$s.t.$

$$\sum_{j}^{m}\sum_{i}^{n} C_i.Q_{ij}(1-\alpha) \le B_j + \left(B_j^{-}\right)$$

$$\sum_{j}^{m}\sum_{i}^{n}\left(Q_{ij}(1-\alpha) - b_{ij}\right) \le F_j$$

$$V_i \le Q_{ij} \le W_i$$

$$\sum_{i}^{n}\sum_{j}^{m} Q_{ij} \le G$$

$$\sum_{i}^{n}\sum_{j}^{m}\frac{D_{ij}}{Q_{ij}} \le N$$

$$b_{ij} \le Q_{ij}$$

$$Q_{ij} > 0, integer, i = 1,2,\dots,n$$

$$b_{ij} \ge 0, integer, j = 1,2,\dots,m$$

$$B_j^{-} \ge 0, \tag{5.16}$$

In this non-exergy sustainable model under carbon tax policy, we have three decision variables, for example, the amount of required loan (additional budget) for each buyer (B_j^{-}), order quantity of each item for each buyer (Q_{ij}), and amount of backorder of each item for each buyer (b_{ij}). In the following subsection, we will consider uncertainty to the non-exergy model in Eq. (5.16).

5.3.5. The inventory model in fuzzy environment

Stochastic modeling methods can solve the inventory model if adequate chronological data exists for ambiguous factors (Aka and Akyüz, 2021). Despite this, it is problematic to have actual and exact random distributions because of the deficiency of chronological data on the coal supply chain in Iran. In the real coal supply chain business world, the market environments are full of uncertainties in a non-stochastic sense (Panja and Mondal 2019). Therefore, the inventory model's critical and unrealistic supposition is that the entire inventory settings operate in a deterministic and definite situation. Uncertainties within the supply chain system, including inflexible sources, the uncertainty of demand, and imprecise predictions, always exist, heading unavoidably to backorders and consequently reducing “customer satisfaction” (Diabat and Al-Salem 2015). One of the successful techniques to diminish these weaknesses is employing “fuzzy set theory (FST),” which is established by Zadeh (1965), creating workable methods to convert “ill-defined” data to mathematical terminologies.

Consequently, the problem investigated in this paper is a fuzzy SVMB multi-item coal supply chain. In this problem, the demands of each buyer and the vendor sales capacity are not well-defined values and are considered imprecise. However, the outcomes must be appropriate for top management in the real business world to determine and apply the consequent responses from fuzzy supply chain. Hence, defuzzification is compulsory (Shekarian et al., 2017). One of the most extensively used techniques is entitled “the linear ranking function method” (the first index) suggested by Yager (1979,1981), which is utilized in this research. The following subsection explains this technique concisely.

5.3.5.1. The linear ranking function method (the first index)

Consider a widespread problem in which its “objective coefficients” and “resources” are fuzzy and stated as follows.

$$\begin{aligned} & Min\, f(z) = \tilde{e}^T z \\ & \quad s.t. \quad A_j z \le \tilde{b}_j, \quad j = 1,2,3,\dots,n \\ & \qquad\qquad z \ge 0, \end{aligned} \tag{5.17}$$

While the sign ‘~’ denotes the fuzziness of the factor, b_j is the restricted resources, z is a vector of the n-dimensional solution, and the quantity of limitations is n. Supposing “triangular fuzzy numbers” for the coefficient matrix $\tilde{e}$, and the vectors on the right-hand side of the restrictions $\tilde{b}_j$, i.e., $\tilde{e}^T = (e_L, e, e_R), \tilde{b} = (b_L, b, b_R)$, the model characterized in (5.17) is converted into its crisp corresponding equation as (Yager 1979,1981):

$$\begin{aligned} & Min\, f(z) = \left(e + \frac{d(R_e) - d(L_e)}{3} \right).z \\ & \quad s.t. \quad A_j z \le \left(b_j + \frac{d(R_b) - d(L_b)}{3} \right), \quad j = 1,2,3,\dots,n \\ & \qquad\qquad z \ge 0, \end{aligned} \tag{5.18}$$

Whereas, for example, for the “triangular fuzzy number” pivotal point e, lateral margins (left and right, respectively) are indicated by $d(L_e) = e - e_L$, and $d(R_e) = e_R - e$ (see Fig. 5.2). Therefore, in this study, the buyers’ demand ($\widetilde{D_{ij}}$) and vendor’s sales capacity ($\tilde{G}$) are considered fuzzy triangular numbers, i.e. $\widetilde{D_{ij}} = \left(D_{ij,L}, D_{ij}, D_{ij,R}\right)$, and $\tilde{G} = (G_L, G, G_R)$.

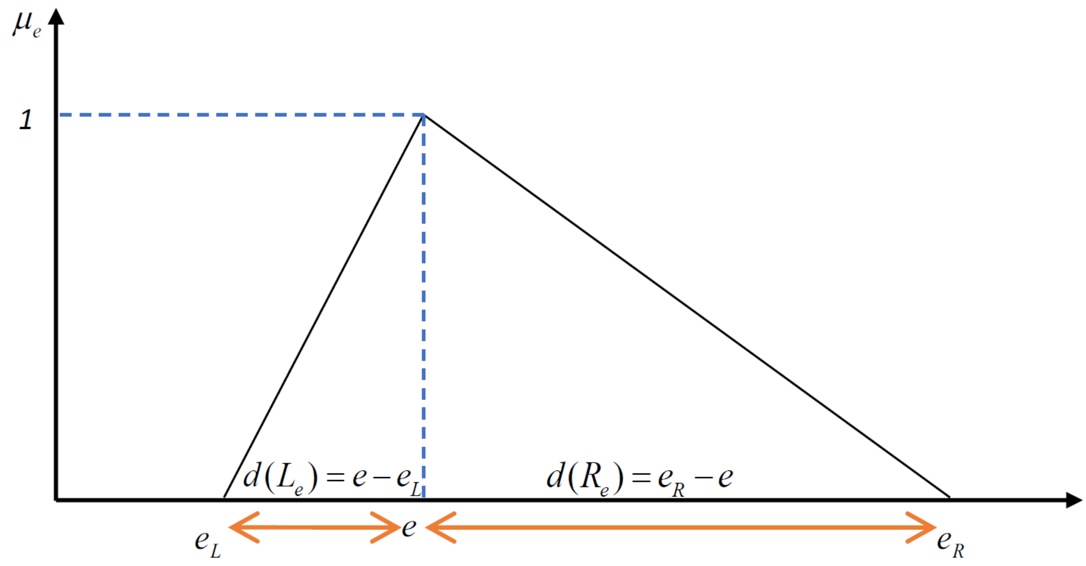

Fig.5.2. Representation of a triangular fuzzy number (TFN)

5.4. Exergy Modeling of fuzzy optimization of SVMB coal supply chain under VMI

The previous section presents a fuzzy monetary sustainable model (minimum Dollar or Euro) for a coal supply chain under a carbon tax strategy. In this section, we employ the EEA method and then convert the monetary model (Eq. 5.16) to the equivalent exergy models.

5.4.1. Extended exergy accounting (EEA)

Exergy analysis involves the management of energy and mass theories with the second law of thermodynamics to draw, estimate, and enhance different energy transfer schemes (Naderi et al., 2021b). Consequently, this analysis can support a system to be more sustainable by reducing the exergy losses happening in energy changeover procedures (Aghbashlo et al., 2018). The EEA, over traditional exergy analysis, has the advantage of connecting the technical production process of specific commodities as well as production processes with their embedded system, such as social system and surrounding environment (Song et al., 2019). Therefore, EEA can facilitate an understanding of the environmental costs from a comprehensive and multidimensional perspective, which bridges the gap about the 'production of value' and distinguishes most economics and biophysical-based methods (Dai et al., 2012). To date, it has been widely accepted as a comprehensive metric that accounts for both physical and monetary costs associated with primary resource consumption. As a result, the EEA refers to a broad "value measure" for "environmental cost formation" in terms of investments and losses of the complex system of society-economy-environment comprising Material (*M*) and Energy (*E*) resources, the labor force (*L*), and capital (*Cap*), in addition to environmental remediation costs (*Env.*). It can be stated as (Jawad et al., 2015; Dai et al., 2012)

$$EEA = ee_M + ee_E + ee_{Cap} + ee_L + ee_{Env} \quad (5.19)$$

Where $(ee_M + ee_E)$ are the exergy of raw materials and energy flows used in producing a product, respectively. The summation of these two exergies $(ee_M + ee_E)$ could be calculated by converting the summation of purchasing costs $(\sum_i^n \sum_j^m C_i D_{ij})$ in the inventory model to the exergy equivalents (Jawad et al., 2015). As mentioned in subsection 5.3.4.2, for simplifying the mathematical model, we ignore the purchasing costs (and therefore exergy equivalents: $ee_M + ee_E$) since it does not affect the model's order quantity (Q_{ij}). All inventory-related costs should be transformed into corresponding exergy amounts to employ the EEA method in an inventory model. The purchasing (C), ordering (A), and keeping (h) costs can be categorized into the summation of three exergy amounts of capital, labor, and environment $(ee_{Cap,i} + ee_{L,i} + ee_{Env,i})$, respectively (Jawad et al. 2018),

$$ee_{Cap,i} = i_{Cap} \times ee_{Cap} \tag{5.20}$$

$$ee_{L,i} = i_L \times ee_L / Labor\ cost \tag{5.21}$$

$$ee_{Env,i} = i_{Env} \times ee_{Env} \tag{5.22}$$

where $i = A, C, or\ h$ are calculated in J/order, J/unit, and J/unit/year, correspondingly. Furthermore (Jawad et al. 2015, 2018; Sciubba 2011),

$$ee_{Cap} = \alpha_x . \beta_x \left(\frac{Ex_{in}}{M_2}\right) \tag{5.23}$$

$$ee_L = \frac{\alpha_x . Ex_{in}}{(NWH)_{total}} \tag{5.24}$$

Where (ee_{Cap}, ee_L) are the specific exergy equivalent of one monetary unit (€, \$, £, ¥) and the unit equivalent exergy of labor, respectively. Moreover, (Ex_{in}) is the total incoming exergy fluctuation (J/yr), can be determined based on the energy budget of the country under study. Regarding Eq. (5.22) for the exergy environment aspect, we follow the method of Chen and Chen (2009), who considered $(ee_{Env} = ee_{Cap})$. Therefore, Eq. (5.22) is changed to $(ee_{Env,i} = i_{Env} \times ee_{Cap})$. It includes any cost paid to get labor, capital, material, and other items used to reduce the damaging environmental effect of producing a product, operating a supply chain, or providing some other service (Jawad et al., 2015).

Now considering Eqs. (5.20)-(5.22), one can calculate the three exergetic values of capital, labor, and environment $(ee_{Cap,i} + ee_{L,i} + ee_{Env,i})$ related to achieving the order cost $A_{(x)}$. Consistent with Sciubba (2011), the EEA method estimates the exergy corresponding to Labour, Money, and Ecological remediation in an item or service by factors of "α_x" and "β_x" along with a few economic quantities as GDP. Such features are vastly guided by labor indicators, population, standard workload, and local and international income. The stated features and exergy counterparts were considered and computed by Sciubba (2011) for several industrial and non-industrial countries.

5.4.2. Applying EEA to fuzzy optimization of SVMB coal supply chain under VMI

Under the carbon tax policy, the exergy equivalent of the total cost is $(TC_{(x)tax} = TC_{(x)1} + TC_{(x)2} + TC_{(x)3} + TC_{(x)4})$. This equivalent can be done with the following formulas (Jawad et al. 2015)

$$A_{(x)i,s} = \left(ee_{Cap,A(i,s)} + ee_{L,A(i,s)} + ee_{Env,A(i,s)}\right) \tag{5.25}$$

$$A_{(x)ij,b} = \left(ee_{Cap,A(ij,b)} + ee_{L,A(ij,b)} + ee_{Env,A(ij,b)}\right) \tag{5.26}$$

$$h_{(x)ij} = \left(ee_{Cap,h(ij)} + ee_{L,h(ij)} + ee_{Env,h(ij)}\right) \tag{5.27}$$

$$s_{(x)1} = s_1 \times \left(ee_{Cap}\right) \tag{5.28}$$

$$s_{(x)2} = s_2 \times \left(ee_{Cap}\right) \tag{5.29}$$

$$C_{(x)i} = \left(ee_{Cap,C(i)} + ee_{L,C(i)} + ee_{Env,C(i)}\right) \tag{5.30}$$

$$A_{(x)ij,t} = A_{ij,t} \times \left(ee_{Cap}\right) \tag{5.31}$$

$$C_{(x)tax} = C_{tax} \times \left(ee_{Cap}\right) \tag{5.32}$$

$$C_{(x)waste} = C_{waste} \times \left(ee_{Cap}\right) \tag{5.33}$$

$$B_{(x)j} = B_j \times \left(ee_{Cap}\right) \tag{5.34}$$

As a result, by employing the above formulas to the objective functions and limitations of the model in Eq. (5.16), it is converted to a fuzzy exergy model under carbon tax policy as follows:

$$\begin{aligned}
TC_{(x)tax} = &\sum_{i}^{n}\sum_{j}^{m}\Bigg[\frac{\widetilde{D_{ij}}}{Q_{ij}}\left(A_{(x)i,s} + A_{(x)ij,b}\right) + \frac{h_{(x)ij}}{2Q_{ij}}\left(Q_{ij}(1-\alpha) - b_{ij}\right)^2 \\
&+ \left(\frac{s_{(x)1}.\,b_{ij}^2}{2Q_{ij}} + \frac{s_{(x)2}.\,b_{ij}.\,\widetilde{D_{ij}}}{Q_{ij}}\right) + \frac{\widetilde{D_{ij}}}{Q_{ij}}\left(A_{(x)ij,t}\right)\Bigg] + \sum_{j}^{m}\left[B_{(x)j}^{-} + \left(int^{-} \times B_{(x)j}^{-}\right)\right] \\
&+ C_{(x)waste} \times \sum_{i}^{n}\sum_{j}^{m}\left[\left(Q_{ij}.\,\alpha\right) + \left(Q_{ij}.\,(1-\alpha).\,\beta\right) + \left(Q_{ij}(1-\alpha).\,(1-\beta).\,\gamma\right)\right] \\
&+ C_{(x)tax} \times \sum_{i}^{n}\sum_{j}^{m}\left[\left(Q_{ij}.\,f_m\right) + \left(\frac{\widetilde{D_{ij}}}{Q_{ij}}.\,L_j.\,f_t\right) + \left(Q_{ij}.\,\widetilde{D_{ij}}.\,f_k\right)\right]
\end{aligned}$$

$s.t.$

$$\sum_{j}^{m}\sum_{i}^{n} C_{(x)i}.\,Q_{ij}(1-\alpha) \le B_{(x)j} + \left(B_{(x)j}^{-}\right)$$

$$\sum_{j}^{m}\sum_{i}^{n}\left(Q_{ij}(1-\alpha) - b_{ij}\right) \le F_j$$

$$V_i \le Q_{ij} \le W_i$$

$$\sum_{i}^{n}\sum_{j}^{m} Q_{ij} \le \tilde{G}$$

$$\sum_{i}^{n}\sum_{j}^{m}\frac{\widetilde{D_{ij}}}{Q_{ij}} \le N$$

$$b_{ij} \le Q_{ij}$$

$$Q_{ij} > 0, integer, i = 1,2,\dots,n$$

$$b_{ij} \ge 0, integer, j = 1,2,\dots,m$$

$$B_{(x)j}^{-} \ge 0, \tag{5.35}$$

In the following section, we suggest four metaheuristic algorithms to solve the fuzzy exergy models in Eq. (5.35) under the EEA technique.

5.5. Solution method

Achieving an "analytical solution" (if any) to the model in Eq. (5.35) is challenging since the model is "nonlinear integer-programming (NIP)" in type, and it is "NP-complete" (Diabat, 2014; Gen and Cheng, 1997; Peng et al., 1998). Put differently, the decision variables are integer, the objective function has a non-derivative arrangement, and exact approaches are overcharged to be applied (Roozbeh Nia et al., 2014). There are three solution search procedures for optimization models such as exact (complete), heuristic, and metaheuristic (random) search algorithms (Shokouhifar and Jalali, 2017). "Exact" techniques and problem-solver tools like LINGO, CPLEX, and GAMS are unproductive on real-size problems regarding needed CPU time (Diabat, 2014; Zahedi et al., 2016). Moreover, even though "heuristics" are not hard to apply and quick in computation time, they do not efficiently examine the search space (Naderi et al., 2021b). To get the maximum accurate outcomes in terms of precision, "metaheuristics" should be employed (Stojanovic et al., 2017). Many academics have effectively manipulated metaheuristic approaches, for example, ant colony optimization (ACO), genetic algorithm (GA), imperialist competitive algorithm (ICA), differential evolution (DE), simulated annealing (SA), particle swarm optimization (PSO) to solve complex optimization models in several areas of engineering, and science subjects (Roozbeh Nia et al., 2017a, 2017b). The type of problem is essential for choosing a good metaheuristic algorithm (Blum et al., 2011). Single-solution algorithms (e.g., SA) exhibit good local search capability, while population-based metaheuristics (e.g., GA) have superior global search capability (Shokouhifar and Jalali, 2017). Therefore, population-based metaheuristics are mostly chosen the others and prove more significant accomplishments in certain circumstances. ACO is among the superior approaches for near optimization manipulated to cope with various models in real-life situations (Gupta and Srivastava, 2020; Guan et al., 2021; Dzalbs and Kalganova, 2020). Besides, GA has confirmed its higher functioning than other metaheuristics for supply chain optimization problems (Saif-Eddine et al., 2019; Saghaeeian and Ramezanian, 2018; Woo and Kim, 2019; Rostami et al., 2020). Hence, we consider four metaheuristic algorithms, including GA, ACO, and SA, as well as a newly suggested algorithm by Mirjalili and Lewis (2016), which is named whale optimization algorithm (WOA) to solve the "exergy fuzzy NIP (EFNIP) problem" modeled in Eq. (5.35). In the following subsections, short explanations primarily supported four metaheuristic algorithms. Afterward, the phases concerned in the proposed solutions are described.

5.5.1. Genetic algorithm (GA)

A genetic algorithm (GA) is an "evolutionary algorithm" created on natural choice and genetics. Holland (1975) proposed GA, and later Goldberg (1989) explained it in detail. GA is universally applied to calculate superior-quality solutions in problem optimization (Poongothai et al., 2021; Rong et al., 2015; Shi, 2014). The authors recommend (Rostamzadeh et al., 2015, Pasandideh et al., 2011; Roozbeh Nia et al., 2014, 2015; Popovic et al., 2014) for the GA algorithm.

5.5.2. The "ant colony optimization (ACO)" algorithm

The ACO algorithm is a metaheuristic algorithm created on "swarm intelligence" (Eberhart and Shi 2000; Van den Bergh 2002) which was first utilized by "Dorigo" in the late 1980s to solve discrete optimization problems (see, for example, Colorni et al., 1991;1992;1994). ACO is the most common optimization algorithm (Gupta and Srivastava 2020; Dorigo and Stutzle 2004). It is established on the performance of ants obtaining food. Ants leave pheromone as they walk and discover their path by walking accompanied by the pheromone evidence. The extent of pheromone accumulation intensifies as ants walk back to the source point with food. Pheromone accumulation on the way back depends on the condition and amount of food brought to the source. Pheromone accumulation /disappearance is precisely associated with the number of ants going on that route. Ants discover the optimal route by tracking the highest pheromone accumulation (De Santis et al., 2018; Booba and Gopal, 2013). The authors refer readers to (Dorigo and Stutzle, 2004; Colorni et al., 1994; Roozbeh Nia et al., 2014) for more detailed facts about the ACO algorithm.

5.5.3. The whale optimization algorithm (WOA)

A recent swarm intelligence optimization algorithm is the whale optimization algorithm (WOA), suggested by Mirjalili and Lewis (2016). This algorithm is created on the specific hunting technique of humpback whales. The method is named bubble-net attacking since whales make unique bubbles near a loop (Goldbogen et al., 2013). Their hunting method has three steps exploring prey, decreasing encircling, and spiral updating place (Mirjalili and Lewis, 2016; Wang et al., 2021; Chen et al., 2020; Lee and Lu, 2020). The WOA has a straightforward principle, operation, and uncomplicated employment since it has few parameters while powerful robustness. Therefore, the WOA algorithm has obtained broad consideration and has gained significant study outcomes (Du et al. 2021; Zhang et al. 2021b; Long et al., 2020). The critical advantage of WOA is that it demands no added tuning parameters to achieve stability in its exploration combined with exploitation (Aala Kalananda and Komanapalli 2021).

5.5.4. The solution processes

The main phases in the recommended solution process of this study are as follows:

Phase 1: Obtain the fuzzy total exergy of the SVMB-VMI coal supply chain of the model in Eq. (5.35) under emission tax policy by each metaheuristic algorithm independently.

Phase 2: Get the superior algorithm for each numerical example.

Phase 3: Find the exact solution of the problem modeled in Eq. (5.35) by GAMS and compare them with metaheuristic ones.

Phase 4: A sensitivity analysis of different percentages for exergy costs in five countries.

An illustration of the chromosomes related to the order quantity and backorder amount of a numerical example (with one vendor and five buyers, which have four items) is offered in Fig. 5.3.

Q_{i1}:	1605	1308	1223	1298
Q_{i2}:	1228	1250	1202	1250
Q_{i3}:	1249	1210	1249	1210
Q_{i4}:	1209	1235	1209	1235
Q_{i5}:	1296	1216	1296	1216

b_{i1}:	196	199	196	199
b_{i2}:	191	195	191	195
b_{i3}:	184	196	184	168
b_{i4}:	177	146	177	146
b_{i5}:	181	167	181	167

Fig.5.3. The demonstration of the chromosomes for the test with four items and five buyers

5.6. Numerical examples

This section gives computational tests, including one real-world coal supply chain case study in Iran and eight related arbitrary cases. We are looking to optimize sustainability in coal supply chain by considering the indirect (hidden) costs, including all three factors simultaneously (using the EEA method) under the carbon tax strategy.

5.6.1 Case study in Iran

The real-world case study includes one vendor and five coal buyers in a supply chain in Iran. Tabas Parvadeh Coal Company (TPCCO), located in Tabas city, is the biggest coal producer in Iran. Consistent with the statistics published by the Iranian Mines and Mining Industries Development and Renovation Organization (IMIDRO), TPCCO extracted 1.232 million tons of coal from March 21, 2019, to January 20, 2020). With about 1.15 billion tons of reserves, Iranian coal mines can deliver up to three million tons of coal concentrate yearly (IEA, clean coal centre, 2020). From another point of view, the production of Steel in Iran is highly reliant on coal since metallurgical coal, or coking coal is an essential component in the steel-making procedure. TPCCO produces four types (grades) of coal, and the company has five key customers (steel producers). These customers are in different cities in Iran, and the public rail transport system does the transportation of order quantities between TPCCO and them. Since the demand of each steel producer (buyer) for each type of coal, as well as the total sales capacity of TPCCO (as a vendor), are not defined precisely, we consider them as triangular fuzzy numbers (see Table 5.2). Moreover, the initial data of the test problem and its equivalent exergy parameters are presented in Tables (5.3)-(5.6), respectively. These input data taken from the Iranian Mines and Mining Industries Development and Renovation Organization (IMIDRO), Sciubba (2011) and Naderi et al. (2021a). For this real case study in Iran, consistent with the informed rates in Sciubba (2011), we take equivalent exergy parameters of Egypt due to the resemblances between Iran and Egypt regarding economic development, population, religion, and culture.

According to Jawad et al. (2015), and after discussing with supply chain directors of TPCCO, it was supposed that each cost $A_{i,S}, A_{ij,b},\ h_{ij}\ and\ C_i$ could be split to *Cap*=30% for money, *L*=60% for labor, and *Env.*=10% for ecological remediation. In Section 5.4, we described the method of EEA and related formulas that we applied to our models. For example, in Table 5.3, the cost of $A_{i,S}$ is assumed €20 for the first item, which includes €6 (20 × 0.30), €12 (20 × 0.60), and €2 (20 × 0.10) (monetary values) for capital (*Cap*=30%), labor (*L*=60%), and environmental (*Env.*=10%) remediation. Moreover, these three monetary numbers are converted to the exergy values based on Eqs. (5.20)-(5.22), and we have $ee_{Cap,A}$ =6×5.68=34.08 (MJ), $ee_{L,A} = 12 \times \frac{3.56}{12} = 3.56(MJ)$ and $ee_{Env,A}$ =2×5.68=11.36(MJ), whereas in total $A_{(x)i,S}$ =49 (*MJ*) in Table 5.6. To show better the performance of our suggested metaheuristic algorithms in solving big-size problems, besides the actual case study, we considered eight arbitrary test problems related to coal supply chain in Iran. These examples have 8 to 1024 types of coal in a supply chain with one vendor and five buyers, like the first case study. The whole initial data of these numerical examples are presented in Appendix Tables (5.A.1)-(5.A.4), respectively. Moreover, all the numerical examples are solved on a PC with an Intel Core i7-7500U CPU with 2.70GHz, and 8.00 GB RAM in Windows 10. "MATLAB" 2017a software is also employed for coding all the algorithms.

Table 5.2: Fuzzy parameters of all buyers for all items in the real case study (example with four items)

Buyer	Item 1	Item 2	Item 3	Item 4
$\widetilde{D_{i1}}$	(330000, 340000, 380000)	(140000, 150000, 190000)	(80000, 90000,130000)	(20000, 30000, 70000)
$\widetilde{D_{i2}}$	(185000, 190000, 225000)	(105000, 110000, 145000)	(65000, 70000, 105000)	(5000, 10000, 45000)
$\widetilde{D_{i3}}$	(137000, 140000, 173000)	(87000, 90000, 123000)	(47000, 50000, 83000)	(7000, 10000, 43000)
$\widetilde{D_{i4}}$	(90000, 95000, 115000)	(80000, 85000, 105000)	(30000, 35000, 55000)	(0, 5000, 25000)
$\widetilde{D_{i5}}$	(75000, 78000, 87000)	(65000, 68000, 77000)	(15000, 18000, 27000)	(0, 3000, 12000)
$\tilde{G} = (35000,40000,60000)$				

Table 5.3: Initial data of the real case study based on capital, labor, and environment values (example with four items)

	Item	value	Unit	Monetary values		
				Cap.	L.	Env.
$A_{i,S}$	1	20	Euro/order	6	12	2
	2	20		6	12	2
	3	20		6	12	2
	4	20		6	12	2
$A_{ij,b}$	1	15	Euro/order	4.5	9	1.5
	2	15		4.5	9	1.5
	3	15		4.5	9	1.5
	4	15		4.5	9	1.5
C_i	1	200	Euro/unit	60	120	20
	2	170		51	102	17
	3	140		42	84	14

	4	100		30	60	10
h_{ij}	1	5	Euro/unit/year	1.5	3	0.5
	2	4		1.2	2.4	0.4
	3	3		0.9	1.8	0.3
	4	3		0.9	1.8	0.3

Table 5.4: Initial data of the real case study (example with four items)

$A_{ij,t} = 10$	$C_{tax} = 200$; $C_{waste} = 10$
$L_j = (655, 1160, 705, 1128, 1067)$	s_1=3, s_2=0
$B_j = (840000, 830000, 820000, 810000, 800000)$	int^-=0.05, int^+=0.02
$F_j = (9600, 9500, 9400, 9300, 9200)$	$f_m = 3.18 \times 10^{-3}$
$N = 1400$	$f_t = 1.4 \times 10^{-5}$
$\alpha = 0.1$; $\beta = 0.1$; $\gamma = 0.1$	$f_k = 5 \times 10^{-5}$
$V_i = 1200$; $W_i = 2500$	

Table 5.5: The exergy parameters used in the inventory analysis of each country (Sciubba, 2011)

	Unit	Iran	Afghanistan	Turkey	Germany	Canada
α_x	-	0.0121	0.0017	0.411	0.557	0.021
β_x	-	2.94	0.07	1.35	1.31	1.95
ee_{Cap}	MJ/€	5.68	1.1	20.51	3.16	3.13
ee_L	MJ/WH	3.56	0.41	91.36	68.25	68.61

Table 5.6: Equivalent exergy parameters of Iran's real case study (example with four items)

$Labor\ cost = 12(€/WH)$	$A_{(x)ij,b} = (36.75, 36.75, 36.75, 36.75)$
$C_{(x)tax} = 1136$	$A_{(x)ij,t} = (85.20)$
$C_{(x)waste} = 56.80$	$h_{(x)ij} = (12.25, 9.80, 7.36, 7.35)$
$s_{(x)1} = 17.04$; $s_{(x)2} = 0$	$C_{(x)i} = (490, 416.50, 343, 245)$
$A_{(x)i,S} = (49, 49, 49, 49)$	$B_{(x)j} = (4771200, 4714400, 4657600, 4600800, 4544000)$

5.6.2 Solving phases and related results

Based on subsection 5.4., the results of each phase of solving procedure for all test problems are presented here.

5.6.2.1. Phase 1: *For an assumed numerical example, independently find the lowest fuzzy total exergy in Eq. (5.35) under emission tax policies by each metaheuristic algorithm.*

Each solution algorithm is performed ten times in this phase for each fuzzy exergy numerical example in Iran. Correspondingly, the lowest fuzzy total exergy and the CPU times (seconds) under the emission tax policy (Eq. 35) are detailed in Tables 5.7 and 5.8, respectively.

5.6.2.2. Phase 2: *Find each test problem's superior individual metaheuristic algorithm under the emission tax policy. The most exemplary metaheuristic algorithm is observed by revealing the proportion distinction between the outcomes.*

Under the emission tax policy, we optimize four objectives simultaneously: the total inventory cost, the total cost associated with the additional required budget of all buyers, the penalty cost of coal waste dumping to the environment, and the total carbon generated by coal supply chain. Using the EEA method, we altered all model economic parameters (Euro) to equivalent exergy values (MJ). Consequently, regarded as four fuzzy exergy objective functions of this model, GA has the lowest fuzzy total exergy in numerical examples of 4-, 32-

, 64- & 128-item (from 2,103,423.54 to 68,268,875.27 MJ). Moreover, WOA is the best algorithm in examples 16-, 256- & 512-item (see Table 5.7). Finally, ACO is superior to other algorithms in examples 8- & 1024-item (4,013,395.32, and 518,222,683.09 MJ). SA has the highest fuzzy total exergy results in all test problems in the same pattern. The percentage difference between the top two algorithms in all numerical examples is less than 1.5% which means their results are close. An evaluation of algorithms in terms of the fuzzy total exergy under emission tax is presented in Fig. 5.4 for our big-size numerical examples (256-, 512- & 1024-items). Likewise, in terms of the computational time (sec.), SA has the shortest CPU time tracked by WOA, GA, and ACO (see Table 5.8 and Fig. 5.5). Furthermore, there is an increasing trend in the improvement percentage of CPU time of the best algorithms with increasing the size of numerical examples (see Fig. 5.6).

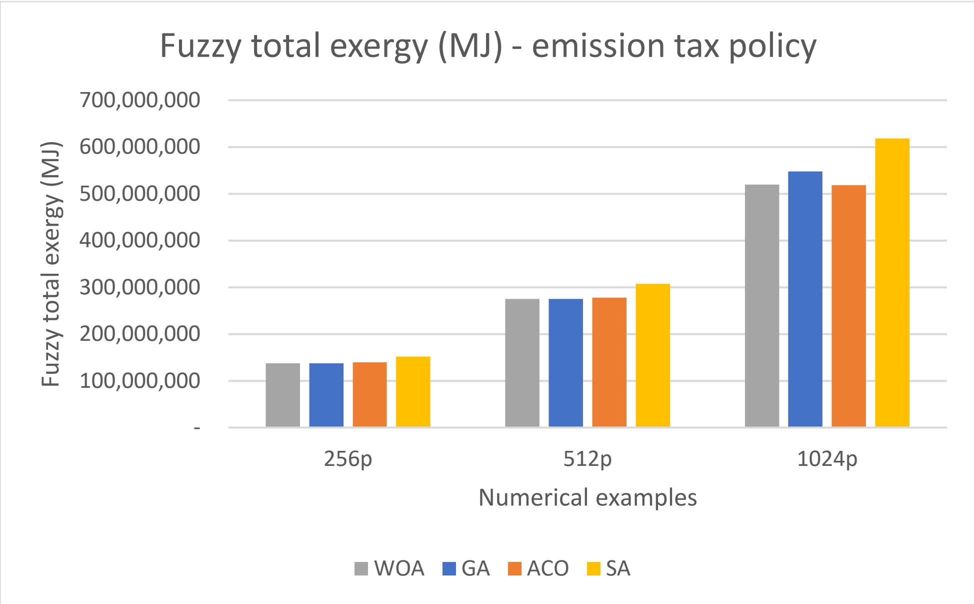

Fig.5.4. The fuzzy total exergy (MJ) comparisons of algorithms for numerical examples (Phase 2)

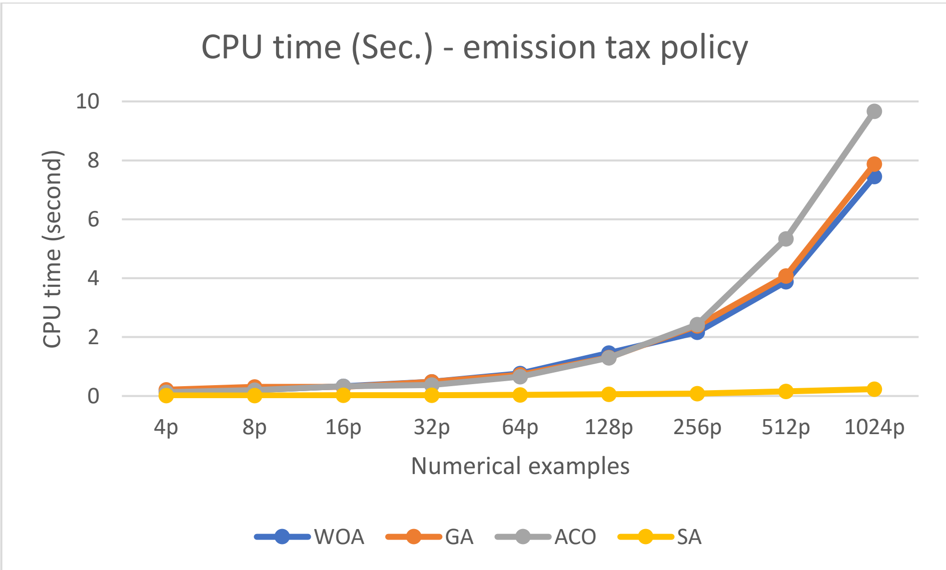

Fig.5.5. The CPU time (second) comparisons of algorithms for numerical examples (Phase 2)

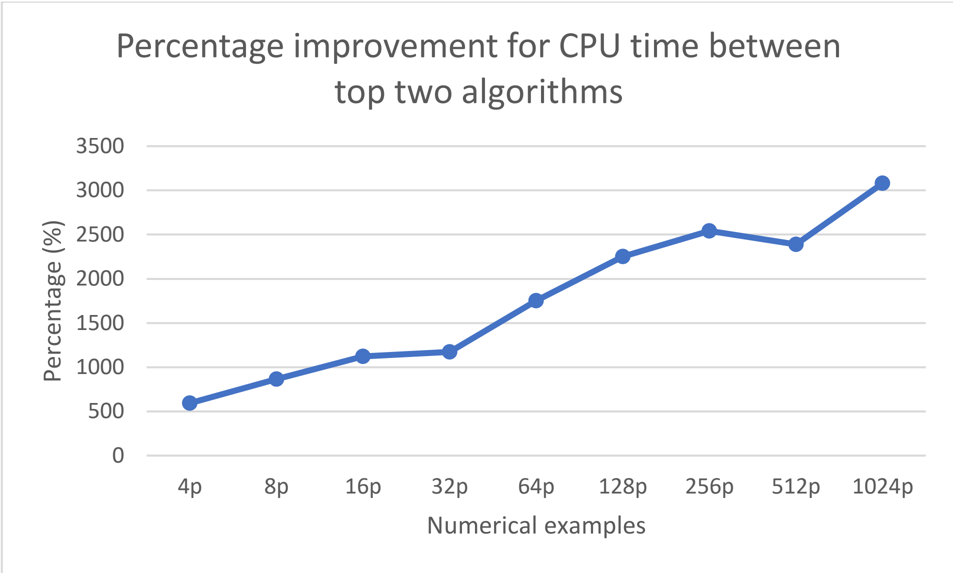

Fig.5.6. The improvement (%) of CPU time between top two algorithms (Phase 2)

Table 5.7: The fuzzy total exergy found by the algorithms (Eq. 5.35) in Iran

No. of items	Fuzzy total exergy (MJ)				The best algorithms	Difference between two bests	Improvement %
	WOA	**GA**	**ACO**	**SA**			
4	2,124,316.51	2,103,423.54	2,149,239.07	2,229,865.34	GA-WOA-ACO-SA	20,892.97	0.99
8	4,018,749.66	4,024,539.99	4,013,395.32	4,484,607.78	ACO-WOA-GA-SA	5,354.34	0.13
16	8,022,249.53	8,111,533.36	8,028,403.95	9,268,720.34	WOA-ACO-GA-SA	6,154.42	0.08
32	17,614,298.66	17,360,279.60	17,771,544.19	18,561,033.21	GA-WOA-ACO-SA	254,019.06	1.46
64	35,155,787.91	34,664,673.10	36,043,124.05	37,192,458.33	GA-WOA-ACO-SA	491,114.81	1.42
128	68,875,447.15	68,268,875.27	69,455,453.56	76,802,024.78	GA-WOA-ACO-SA	606,571.88	0.89
256	137,679,030.04	137,723,302.18	139,170,388.10	152,060,059.56	WOA-GA-ACO-SA	44,272.14	0.03
512	275,080,936.61	275,221,821.44	277,971,334.66	307,251,073.62	WOA-GA-ACO-SA	140,884.83	0.05
1024	519,346,028.93	547,658,039.42	518,222,683.09	618,273,942.66	ACO-WOA-GA-SA	1,123,345.84	0.22
Exact method's result (4 items) = 2,063,660.06 (MJ); Difference with GA=39,763.48; % Error=1.92							

Table 5.8: The CPU times of solving test problems by the algorithms (Eq. 5.35) in Iran

No. of items	CPU time (second)				The best algorithms	Difference between two bests	Improvement %
	WOA	**GA**	**ACO**	**SA**			
4	0.159	0.212	0.129	0.019	SA-ACO-WOA-GA	0.11	593.28
8	0.200	0.306	0.199	0.021	SA-ACO-WOA-GA	0.18	865.94
16	0.331	0.313	0.326	0.026	SA-GA-ACO-WOA	0.29	1121.92
32	0.486	0.480	0.375	0.029	SA-ACO-GA-WOA	0.35	1173.23
64	0.762	0.720	0.652	0.035	SA-ACO-GA-WOA	0.62	1750.68
128	1.464	1.312	1.302	0.055	SA-ACO-GA-WOA	1.25	2252.62
256	2.164	2.387	2.421	0.082	SA-WOA-GA-ACO	2.08	2542.30
512	3.885	4.076	5.333	0.156	SA-WOA-GA-ACO	3.73	2387.74
1024	7.451	7.874	9.669	0.234	SA-WOA-GA-ACO	7.22	3079.42
Exact method's result (4 items) = 4.186 Sec.; Difference with GA=3.97 Sec.; % Error= 1876.30							

5.6.2.3. Phase 3: *Find the "exact" results and compare them with metaheuristic ones.*

To develop a good knowledge and understanding of the solution obtained through the suggested algorithms, a solution may be contrasted with an "exact method." This "exact result" can be achieved through exact optimizer software such as "GAMS" or an optimization library in "Python." In this study, the proposed mathematical model (Eq. 5.35) under emission tax policy is solved in small sizes (example with four items) by GAMS. A comparison with the best metaheuristic algorithm is made.

For the 4-item numerical example under emission tax policy and Eq. (5.35), the exact result for the fuzzy total exergy is 2,063,660.06 (MJ), while the outcome of the best metaheuristic algorithm (GA) for this example is 2,149,239.07 (MJ). Consequently, the difference between them is 39,763.48 (MJ), and the percentage penalty or error is 1.92%. Because the percentage penalty is minor, indicating the fair dominance of the solutions obtained through the best-suggested algorithm (Cárdenas-Barrón et al., 2012), as it is remarkably close to the exact method (see Table 5.7 and Fig. 5.7). Considering computation time, the difference between the exact method and GA is 3.97 (Sec.), while the percentage penalty is 1876.30%. Similarly, it means the metaheuristic algorithm (GA) solved the tax policy model more quickly (see Table 5.8 and Fig. 5.8). Moreover, the diagrams of fuzzy total exergy by the suggested algorithms are presented in Fig. 5.9.

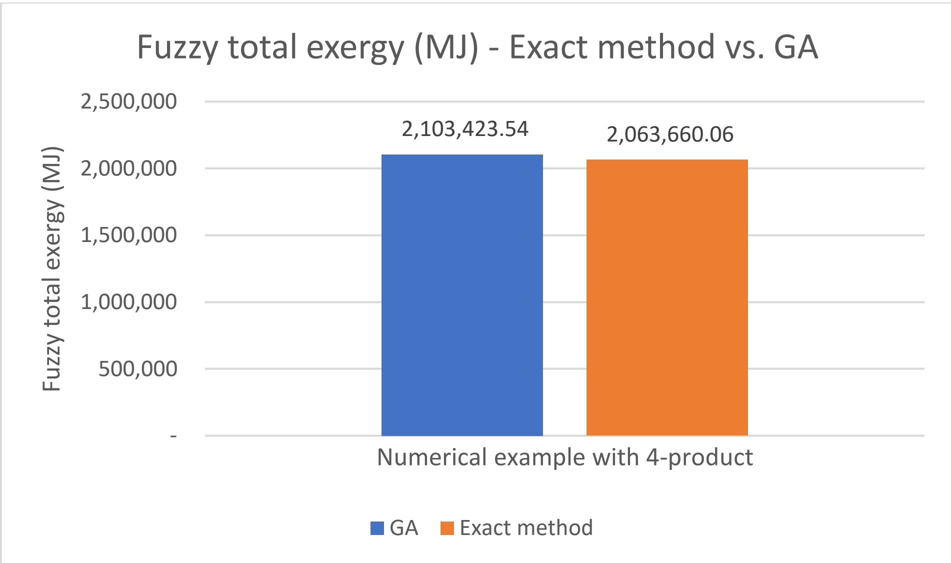

Fig.5.7. Comparison of the fuzzy total exergy between exact method and the best metaheuristic algorithm (Phase 3)

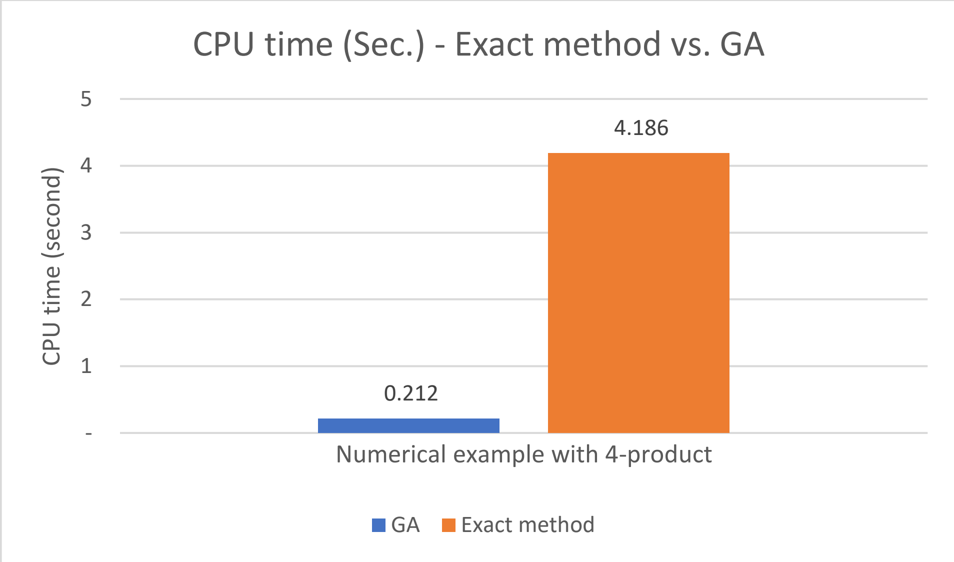

Fig.5.8. Comparison of CPU time between exact method and the best metaheuristic algorithm (Phase 3)

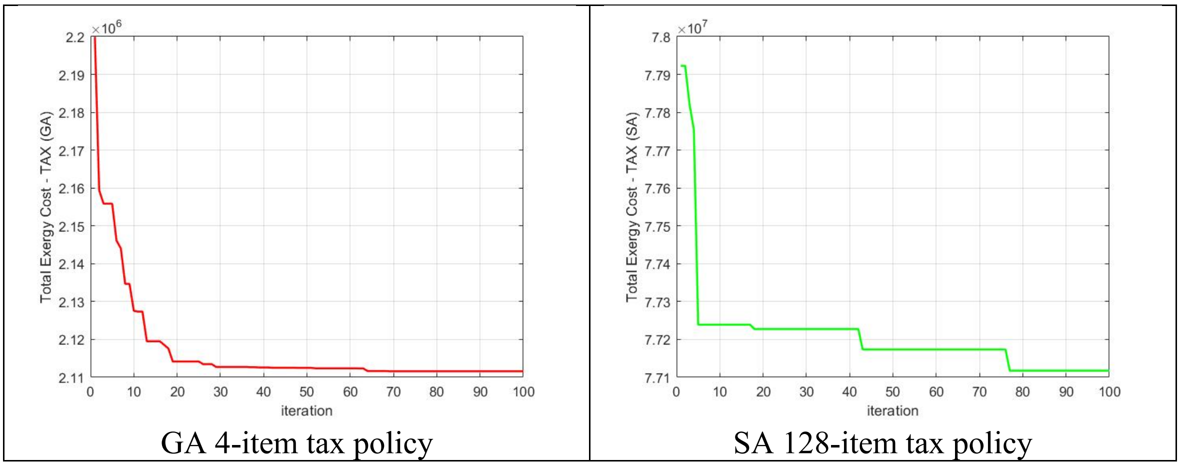

Fig.5.9. The diagrams of fuzzy total exergy by the suggested algorithms (Phases 2 & 3)

5.6.2.4. Phase 4: *A sensitivity analysis of different percentages for exergy cost components in five countries.*

In this phase, we balance financial and sustainable benefits for coal supply chain enterprises. As our proposed models are sustainable, we are looking to adjust the exergy percentage for capital, labor, and environmental remediation by a sensitivity analysis to decrease the fuzzy total exergy and carbon emission more than before. Moreover, to get more insight into this issue, we compare the sensitivity analysis of coal supply chain in Iran with two neighboring countries (Afghanistan and Turkey) and two developed countries such as Germany and Canada. We assume the same coal supply chain and items for all five countries. Previous step assumed that each cost $A_{i,S}, A_{ij,b}, \ h_{ij} \ and \ C_i$ could be allocated to *Cap*=30% for money, *L*=60% for labor, and *Env.*=10% for ecological remediation (consider it as Set A). Now, in this step to get more insight, we have changed these percentages to make five different exergy sets (see Table 5.9), including A (30-60-10), B (50-30-20), C (20-50-30), D (30-20-50), and E (33-

33-33). Considering each exergy set, we obtained the fuzzy total exergy for a 4-item test problem under the carbon tax policy for coal supply chain in each country using the GAMS. Moreover, the exergy parameters of five countries are presented in Table 5.5, and all sensitivity results are presented in Table 5.9. In the following, we explain the results in detail.

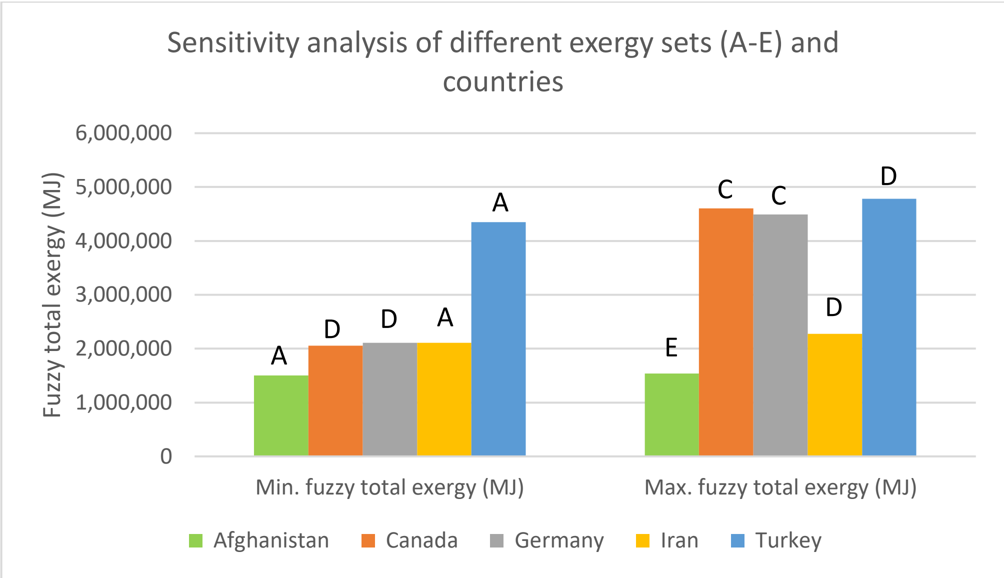

Fig.5.10. Sensitivity analysis - Min. & Max. of the total fuzzy exergy of each country (Phase 4)

5.6.2.4.1 Analysis of each country

Considering Table 5.9 and Fig. 5.10, for coal supply chain in each country, we have:

- **Afghanistan:** in this country, the top exergy components are Set A (30-60-10) since more exergy weight is assigned for Labor (60%) and less for Environment (10%). It created the minimum fuzzy total exergy of 1,504,757.85 (MJ) for coal supply chain. Furthermore, the worst exergy components in Afghanistan are Set E (33-33-33) when the same weights (33%) are assigned to Capital, Labor, and Environment with 1,540,156.67 (MJ).
- **Canada:** The best exergy components are Set D (30-20-50) when Environment has 50% weight, going along with Capital (30%) and Labor (20%), respectively. It created the minimum fuzzy total exergy of 2,055,844.41 (MJ) for Canada. Similarly, the weakest exergy components are Set C (20-50-30) when more exergy weight is supposed for Labor (50%), which generated the greatest fuzzy total exergy of 4,606,446.58 (MJ).
- **Germany:** Like Canada, the best exergy components in Germany are Set D (30-20-50), when 50% of weight is assigned to Environment. It produced the minimum fuzzy total exergy of 2,109,044.72 (MJ) for coal supply chain. Moreover, the unhealthiest exergy components are Set C (20-50-30) when 50% weight is assigned to Labor, which made the maximum fuzzy total exergy of 4,492,797.20 (MJ).
- **Iran:** The top exergy components are Set A (30-60-10), as Labor has 60% while Environment has only 10%. It made the minimum fuzzy total exergy of 2,110,974.62 (MJ). The weakest exergy components in Iran are Set D (30-20-50), when 50% weight is allocated to Environment, which created the maximum fuzzy total exergy of 2,274,445.14 (MJ).

- **Turkey:** Like Iran, the best exergy components in Turkey are Set A (30-60-10), while more exergy percentage is given to Labor (60%). It established the least amount of fuzzy total exergy with 4,351,316.03 (MJ) for coal supply chain. Likewise, the worst exergy components are Set D (30-20-50) when more weight is provided to the Environment (50%), which generated the highest fuzzy total exergy of 4,780,003.95 (MJ).
- Respecting Table 5.9 and Fig. 5.10, the minimum total exergy (MJ) in coal supply chain of each country is as follow Afghanistan (1,504,757.85), Canada (2,055,844.41), Germany (2,109,044.72), Iran (2,110,974.62), and Turkey (4,351,316.03).
- Among all presented countries, the coal supply chain in Afghanistan has the lowest total exergy (1,504,757.85 MJ), followed by Canada, Germany, Iran, and Turkey, respectively (see Fig. 5.10).
- Moreover, coal supply chain in Turkey creates the highest total exergy under exergy Sets of B (50-30-20), D (30-20-50) and E (33-33-33), among other countries. Similarly, Canada, under exergy Sets of A (30-60-10) and C (20-50-30), forms the greatest total exergy in coal supply chain (see Table 5.9).

5.6.2.4.2 Analysis of each exergy set

Considering Table 5.9 and Fig. 5.11, for each exergy set, we have:

- **Exergy Set A (30%-60%-10%):** In this set, more weight is assigned to Labor (60%) and only 10% to Environment. Although this set works well for coal supply chain in Afghanistan, with the minimum total exergy of 1,504,757.85 (MJ), Canada has 4,606,147.99 (MJ).
- **Exergy Set B (50%-30%-20%):** In this set, more weight is assumed for Capital (50%) along with Labor (30%) and Environment (20%), respectively. Regardless of coal supply chain in Turkey (4,654,099.79 MJ), exergy set B operates well in Afghanistan with 1,533,788.62 (MJ).
- **Exergy Set C (20%-50%-30%):** In this set, Labor has 50% weight, followed by Environment (30%) and Capital (20%), respectively. Exergy set C performs well in coal supply chain in Afghanistan (1,533,954.88 MJ), even though in Canada, the total exergy is 4,606,446.58 (MJ).
- **Exergy Set D (30%-20%-50%):** In this set, Labor has only 20% while 50% is for Environment. Despite the high result in Turkey with 4,780,003.95 (MJ), exergy set D runs well in Afghanistan with 1,512,552.55 (MJ).
- **Exergy Set E (33%-33%-33%):** In this set, all three exergy components have equal 33% weight. Although exergy set E does not perform well in Turkey with 4,602,880.36 (MJ), it runs well in Afghanistan with 1,540,156.67 (MJ).
- Moreover, all exergy Sets (A-E) generated the minimum total exergy for coal supply chain in Afghanistan (see Fig. 5.11).

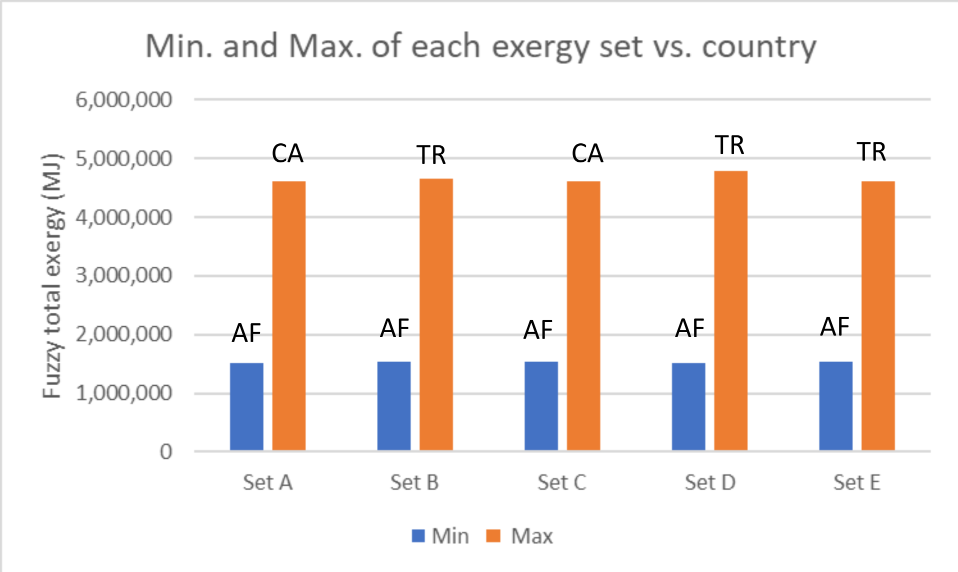

Fig.5.11. Sensitivity analysis - Min. and Max. of each exergy set (Phase 4)

Table 5.9: Sensitivity analysis of different percentages for exergy costs in five countries (example with four items)

%(Cap-L-Env.)		Fuzzy total exergy (Emission Tax) MJ					Min.	Country min.	Max.	Country max.
		AF*	**CA**	**GE**	**IR**	**TR**				
Set A	**30-60-10**	1,504,757.85	4,606,147.99	4,479,364.93	2,110,974.62	4,351,316.03	1,504,757.85	AF	4,606,147.99	CA
Set B	**50-30-20**	1,533,788.62	2,667,490.61	2,655,420.96	2,230,157.59	4,654,099.79	1,533,788.62	AF	4,654,099.79	TR
Set C	**20-50-30**	1,533,954.88	4,606,446.58	4,492,797.20	2,234,708.24	4,412,490.90	1,533,954.88	AF	4,606,446.58	CA
Set D	**30-20-50**	1,512,552.55	2,055,844.41	2,109,044.72	2,274,445.14	4,780,003.95	1,512,552.55	AF	4,780,003.95	TR
Set E	**33-33-33**	1,540,156.67	3,007,167.24	2,928,353.16	2,220,750.94	4,602,880.36	1,540,156.67	AF	4,602,880.36	TR
Balanced point	**Min.**	**1,504,757.85**	**2,055,844.41**	**2,109,044.72**	**2,110,974.62**	**4,351,316.03**	Min. Min.		Max. Max.	
	Set min	**A**	**D**	**D**	**A**	**A**	1,504,757.85	AF	4,780,003.95	TR
	Max.	1,540,156.67	4,606,446.58	4,492,797.20	2,274,445.14	4,780,003.95	Set A		Set D	
	Set max	**E**	**C**	**C**	**D**	**D**				

*AF: Afghanistan, CA: Canada, GE: Germany, IR: Iran, TR: Turkey

5.7. Conclusions and future research works

Classical models do not consider inventory systems' unseen (indirect) costs. In fact, in earlier research, the meaning of the cost is workflow-associated cost aspects, and it is limited to finding a study that evaluates the supply chain in terms of Joules (rather than conventional monetary objectives) and, at the same time, assesses all sustainability features, for example, economic, labour, and environmental. Moreover, to the best of the authors' knowledge, no exergy analysis approach like the EEA in the literature take into account the carbon tax strategy in supply chain. With increasing awareness of global warming and environmental issues, problems such as carbon emission and imperfect quality items discarded to the environment related to coal mining and steel manufacturing have become crucial indicators of coal supply chain evaluation. Moreover, there is a lack of research in the literature that evaluates the supply chain under a carbon tax strategy with vague parameters such as buyer demand. Finally, there is an absence of studies that evaluate the sustainability of coal supply chains in developed and developing countries with a carbon tax strategy in terms of Joules.

Hence, this research considers the studies of Jawad et al. (2015) and Naderi et al. (2021a) and, more precisely, develops it into a multi-item multi-constraint multi-buyer EOQ model in coal supply chain under uncertainty conditions. This supply chain has a single vendor and multi-buyer (SVMB) that coordinate with the VMI approach and considers inventory stockout as a backorder. Additionally, to make the model green, a penalty cost for imperfect quality items disposal to the environment is considered. By employing the EEA method and Mega-Joules (*MJ*) as a universal unit of measure, the total exergy of the coal supply chain can be calculated. Additionally, a carbon tax is utilized to assess the sustainability performance of coal supply chain. Four metaheuristic algorithms were suggested to solve the model, including GA, ACO, SA, and WOA, and their results were compared with the exact method, like GAMS. In the last part, a sensitivity analysis with different exergy values (for Capital, Labor, and Environment) was done to find the best exergy set for coal supply chain in five countries, including Iran, Afghanistan, Turkey, Germany, and Canada.

In this study, we presented three research questions (in Section 5.1) and attempted to answer them.

Q1. Does incorporating a carbon tax strategy with the EEA method in coal supply chain trigger financial benefits and sustainability advantages?

In subsection 5.3.4, we developed a non-exergy mathematical model of the coal supply chain for carbon tax strategy. Then the model has converted to a fuzzy model in subsection 5.3.5, and finally, a recent supply chain assessment method entitled the EEA (regarding Joules) was used in section 4. This technique covers energy and material's primary aggregate exergy subject and costs related to monetary externality (labor and capital) and environmental externality (environmental aspects). Consequently, this technique could promote both the financial system and the environment. Four famous metaheuristic algorithms (WOA, GA, ACO, and SA) are employed to solve the exergy fuzzy nonlinear integer programming (EFNIP) problem modelled in Eq. (5.35). Concerning this model, and the results in subsection 6.2 for all test problems (from 4-item to 512-item), GA and WOA are the top two algorithms with the lowest fuzzy total exergy except for test problem 1024-item, which ACO is superior. When comparing the results with the exact method (GAMS), there is a small percentage error (1.92%) between them. Therefore, it could validate the results of metaheuristic algorithms in this study. The percentage penalty in CPU running time between the exact method and suggested metaheuristic algorithms is high while solving the model by the metaheuristic algorithm (GA) is faster.

Q2. The coal supply chain in developing countries is supposed to have the lowest cost overall; however, in terms of sustainability (social, economic, and environmental aspects) and considering Joules rather than monetary objectives, does this assumption remain accurate?

Considering the sensitivity analysis in subsection 5.6.2.4, we evaluated the sustainability of coal supply chain in five countries, such as Iran, Afghanistan, Turkey, Germany, and Canada (see Table 5.9). Subject to the findings, coal supply chains in Canada and Germany have better sustainability performance in Joules than Iran and Turkey. For example, the lowest total exergy of a coal supply chain in Canada and Germany are 2,055,844.41 and 2,109,044.72 (MJ), respectively, while in Iran and Turkey, they are 2,110,974.62 and 4,351,316.03 (MJ), respectively. The explanation is that conventional supply chain evaluation techniques consider monetary measures while the technique of EEA reflects all three characteristics of sustainability (Labour, Money, and Environmental remediation) in goods or services. Furthermore, in our study, there is one exceptional country; the coal supply chain in Afghanistan has far better sustainability performance than all countries, with the lowest total exergy equal to 1,504,757.85 (MJ). The reason behind this outstanding result is that the exergy parameters of Capital ($ee_{Cap} = 1.1, MJ/Euro$) and Labour ($ee_L = 0.41, MJ/WH$) in Afghanistan are less than other countries in this study (see Table 5.5).

Q3. Which percentage set of exergy components (social, economic, and environmental characteristics) creates the lowest total exergy of supply chain? which country has more sustainable conditions for coal supply chain?

Regarding subsection 5.6.2.4 and Table 5.9, it is examined that with carbon tax strategy, exergy Set A (30-60-10) that is assigned more weight (60%) on Labor and less (10%) on Environment could create the lowest fuzzy total exergy in coal supply chain of the countries such as Afghanistan, Iran, and Turkey. Moreover, exergy Set D (30-20-50), which is given more weight (50%) to Environment, followed by 30% to Capital and only 20% to Labor, could form the lowest fuzzy total exergy in Canada and Germany. As mentioned in the previous answer, with 1,504,757.85 (MJ), Afghanistan has the finest sustainable coal supply chain among all countries in this study, followed by Canada, Germany, and Iran with 2,055,844.41; 2,109,044.72 and 2,110,974.62 (MJ), respectively. Among all countries in this study, the weakest sustainability condition (highest fuzzy total exergy) for coal supply chain belongs to Turkey, with 4,351,316.03 (MJ).

In contrast to the conventional financial and commercial models, the outcomes of our analysis propose that even though we supposed that the factors of inventory models are unchanged for the five coal supply chains, sustainability improvement could be achieved because of the adjustments among exergy's inflows/outflows in the five countries. It means no fixed exergy components amount creates the highest sustainability in all countries. For example, based on our results in Table 5.9, considering more weight (50%) to Environment and only 20% to Labor as set D (30-20-50) creates the maximum sustainability for coal supply chain in Canada and Germany (with 2,055,844.41 and 2,109,044.72 MJ) and at the same time the weakest sustainability for Iran and Turkey (with 2,110,974.62 and 4,351,316.03 MJ).

Another point is that, for developed countries like Canada and Germany, improving the sustainability of coal supply chain in terms of Joules takes place when more weight is given to the exergy of the Environment (for example, 50% in Set D) and less on exergy of Labour. In contrast, more emphasis on the exergy of Labor and less on the Environment (for example, Labor=60%, Environment=10% in Set A) for developing countries creates sustainability improvement. Therefore, decision-makers in coal supply chain could realize that adjusting which sustainability aspect (Capital, Labor and Environment) is more important in each country.

Regarding Table 5.9, on the one hand, the sustainability performance of coal supply chain in Afghanistan is 36.62% better than in Canada. Afghanistan has the best sustainability condition for coal supply chain with only 1,504,757.85 (MJ). Considering Table 5.5, one can conclude that all exergy parameters in Afghanistan, such as ($ee_{Cap}, ee_L, \alpha_x, \beta_x$) are less than other countries. On the other hand, the mentioned exergy parameters (precisely ee_{Cap}, ee_L) in Turkey are higher than other countries, which creates the weakest sustainability condition. Therefore, these exergy parameters significantly impact the total exergy cost of coal supply chain in each country. Consequently, another way to improve the sustainability in each country is to find ways to decrease exergy parameters. If we look at Eqs. (5.23) and (5.24), exergy parameters of (ee_{Cap}, ee_L) are dependent on two econometric coefficients (α_x, β_x) as well as (Ex_{in}). As mentioned in subsection 4.1, these are related to the type of societal organization, the historical period, the technological level, the pro-capital resource consumption, and the geographic location of the country they are (Sciubba, 2011). Adjusting ($\alpha_x, \beta_x, Ex_{in}$), if possible, is a complicated mission that demands great attempts from all shareholders, governments, individuals, societies, business organisations, scientists, etc. For example, controlling the importing and exporting of goods from and to the country, extraction of ores and minerals placed within the control level of the society. Individuals, societies, and business organisations can support in this way by promoting locally made goods. This, also, can enhance the rate of labor force in the country by establishing more job opportunities (Jawad et al., 2018). Moreover, effective productivity (output per hour worked) growth can boost per capita GDP and income of a country. Interested readers are encouraged to study Sciubba (2011) for more information.

Moreover, looking at exergy equations in Section 4 (For example, Eqs. 5.25-5.34), all exergy parameters in Table 5.5 have a direct relation to the cost elements of the inventory models (such as ordering, purchasing, and holding), and accordingly highly impact on the total exergy functioning of a coal supply chain. Therefore, decreasing the cost elements of the inventory model in coal supply chain is another way to improve sustainability. For example, employing stock classification, shorter order cycles, supplier lead time reduction, eliminating obsolete inventory, apply a Just-in-Time inventory system, and monitor key performance indicators.

Top management in coal supply chains must reduce waste resources such as energy, labor, material, and pollution to diminish the negative impact on coal supply chain sustainability. Additionally, a coal supply chain may need to find the potential prospects to moderate its total exergy cost without losing its benefits or customers. From another point of view, these results may encourage the government to regulate sustainability policies better. It means reducing the negative impacts of economic growth without losing the speed of development (a win-win strategy).

The following topics for future research are suggested:

(a) The multi-objective model can be considered.
(b) Economic production quantity (EPQ) or a production system can be considered.
(c) Lead times can be included.

(d) Quantity discounts in cost per unit of items can be permitted.
(e) Other emission gas such as SO2 and NOx could be considered.
(f) Other carbon policies like cap, trade or offset can be investigated.
(g) Fuzzy parameters can be considered as an Interval type 2.
(h) Multi-echelon supply chains such as single-buyer multi-supplier and multi-buyer multi-supplier supply chains can be investigated.
(i) Other new meta-heuristic algorithms such as sperm whale algorithm (SWA), sine cosine algorithm (SCA), moth-flame optimization algorithm (MFO), ant lion Optimizer (ALO), and differential evolution (DE) can also be used.

Postscripts:

This chapter considered carbon tax policy for coal SC to improve the sustainability of coal SC in both developed and developing countries by incorporating extended exergy accounting. In the next chapter, carbon trade policy will be applied to coal SC. Additionally, carbon cap and offset policies will be presented in Chapters 7 and 8, respectively as additional material.

Paper Appendix-Chapter 5

Table 5.A.1. Fuzzy demands of all buyers for all items (a vendor and five buyers)

Item (i)	D_{i1}	D_{i2}	D_{i3}	D_{i4}	D_{i5}
1	(330000, 340000, 380000)	(185000, 190000, 225000)	(137000, 140000, 173000)	(90000, 95000, 115000)	(75000, 78000, 87000)
2	(140000, 150000, 190000)	(105000, 110000, 145000)	(87000, 90000, 123000)	(80000, 85000, 105000)	(65000, 68000, 77000)
3	(80000, 90000,130000)	(65000, 70000, 105000)	(47000, 50000, 83000)	(30000, 35000, 55000)	(15000, 18000, 27000)
4	(20000, 30000, 70000)	(5000, 10000, 45000)	(7000, 10000, 43000)	(0, 5000, 25000)	(0, 3000, 12000)
5	(330000, 340000, 380000)	(185000, 190000, 225000)	(137000, 140000, 173000)	(90000, 95000, 115000)	(75000, 78000, 87000)
6	(140000, 150000, 190000)	(105000, 110000, 145000)	(87000, 90000, 123000)	(80000, 85000, 105000)	(65000, 68000, 77000)
7	(80000, 90000,130000)	(65000, 70000, 105000)	(47000, 50000, 83000)	(30000, 35000, 55000)	(15000, 18000, 27000)
8	(20000, 30000, 70000)	(5000, 10000, 45000)	(7000, 10000, 43000)	(0, 5000, 25000)	(0, 3000, 12000)
9	(330000, 340000, 380000)	(185000, 190000, 225000)	(137000, 140000, 173000)	(90000, 95000, 115000)	(75000, 78000, 87000)
10	(140000, 150000, 190000)	(105000, 110000, 145000)	(87000, 90000, 123000)	(80000, 85000, 105000)	(65000, 68000, 77000)
11	(80000, 90000,130000)	(65000, 70000, 105000)	(47000, 50000, 83000)	(30000, 35000, 55000)	(15000, 18000, 27000)
12	(20000, 30000, 70000)	(5000, 10000, 45000)	(7000, 10000, 43000)	(0, 5000, 25000)	(0, 3000, 12000)
13	(330000, 340000, 380000)	(185000, 190000, 225000)	(137000, 140000, 173000)	(90000, 95000, 115000)	(75000, 78000, 87000)
14	(140000, 150000, 190000)	(105000, 110000, 145000)	(87000, 90000, 123000)	(80000, 85000, 105000)	(65000, 68000, 77000)
15	(80000, 90000,130000)	(65000, 70000, 105000)	(47000, 50000, 83000)	(30000, 35000, 55000)	(15000, 18000, 27000)
16	(20000, 30000, 70000)	(5000, 10000, 45000)	(7000, 10000, 43000)	(0, 5000, 25000)	(0, 3000, 12000)
17	(330000, 340000, 380000)	(185000, 190000, 225000)	(137000, 140000, 173000)	(90000, 95000, 115000)	(75000, 78000, 87000)
18	(140000, 150000, 190000)	(105000, 110000, 145000)	(87000, 90000, 123000)	(80000, 85000, 105000)	(65000, 68000, 77000)
19	(80000, 90000,130000)	(65000, 70000, 105000)	(47000, 50000, 83000)	(30000, 35000, 55000)	(15000, 18000, 27000)
20	(20000, 30000, 70000)	(5000, 10000, 45000)	(7000, 10000, 43000)	(0, 5000, 25000)	(0, 3000, 12000)
21	(330000, 340000, 380000)	(185000, 190000, 225000)	(137000, 140000, 173000)	(90000, 95000, 115000)	(75000, 78000, 87000)
22	(140000, 150000, 190000)	(105000, 110000, 145000)	(87000, 90000, 123000)	(80000, 85000, 105000)	(65000, 68000, 77000)
23	(80000, 90000,130000)	(65000, 70000, 105000)	(47000, 50000, 83000)	(30000, 35000, 55000)	(15000, 18000, 27000)
24	(20000, 30000, 70000)	(5000, 10000, 45000)	(7000, 10000, 43000)	(0, 5000, 25000)	(0, 3000, 12000)
25	(330000, 340000, 380000)	(185000, 190000, 225000)	(137000, 140000, 173000)	(90000, 95000, 115000)	(75000, 78000, 87000)

26	(140000, 150000, 190000)	(105000, 110000, 145000)	(87000, 90000, 123000)	(80000, 85000, 105000)	(65000, 68000, 77000)
27	(80000, 90000,130000)	(65000, 70000, 105000)	(47000, 50000, 83000)	(30000, 35000, 55000)	(15000, 18000, 27000)
28	(20000, 30000, 70000)	(5000, 10000, 45000)	(7000, 10000, 43000)	(0, 5000, 25000)	(0, 3000, 12000)
29	(330000, 340000, 380000)	(185000, 190000, 225000)	(137000, 140000, 173000)	(90000, 95000, 115000)	(75000, 78000, 87000)
30	(140000, 150000, 190000)	(105000, 110000, 145000)	(87000, 90000, 123000)	(80000, 85000, 105000)	(65000, 68000, 77000)
31	(80000, 90000,130000)	(65000, 70000, 105000)	(47000, 50000, 83000)	(30000, 35000, 55000)	(15000, 18000, 27000)
32	(20000, 30000, 70000)	(5000, 10000, 45000)	(7000, 10000, 43000)	(0, 5000, 25000)	(0, 3000, 12000)

Table 5.A.2. Initial data of all test problems (monetary value) and their equivalent exergy values (MJ) for Iran

Item	Cost values (€)					Exergy equivalent (MJ)				
(i)	$A_{i,S}$	$A_{ij,b}$	$A_{ij,t}$	h_{ij}	C_i	$A_{(x)i,S}$	$A_{(x)ij,b}$	$A_{(x)ij,t}$	$h_{(x)ij}$	$C_{(x)i}$
1	20	15	10	5	200	49	36.75	85.20	12.25	490
2	20	15	10	4	170	49	36.75	85.20	9.80	416.50
3	20	15	10	3	140	49	36.75	85.20	7.36	343
4	20	15	10	3	100	49	36.75	85.20	7.35	245
5	20	15	10	5	200	49	36.75	85.20	12.25	490
6	20	15	10	4	170	49	36.75	85.20	9.80	416.50
7	20	15	10	3	140	49	36.75	85.20	7.36	343
8	20	15	10	3	100	49	36.75	85.20	7.35	245
9	20	15	10	5	200	49	36.75	85.20	12.25	490
10	20	15	10	4	170	49	36.75	85.20	9.80	416.50
11	20	15	10	3	140	49	36.75	85.20	7.36	343
12	20	15	10	3	100	49	36.75	85.20	7.35	245
13	20	15	10	5	200	49	36.75	85.20	12.25	490
14	20	15	10	4	170	49	36.75	85.20	9.80	416.50
15	20	15	10	3	140	49	36.75	85.20	7.36	343
16	20	15	10	3	100	49	36.75	85.20	7.35	245
17	20	15	10	5	200	49	36.75	85.20	12.25	490
18	20	15	10	4	170	49	36.75	85.20	9.80	416.50
19	20	15	10	3	140	49	36.75	85.20	7.36	343
20	20	15	10	3	100	49	36.75	85.20	7.35	245
21	20	15	10	5	200	49	36.75	85.20	12.25	490
22	20	15	10	4	170	49	36.75	85.20	9.80	416.50
23	20	15	10	3	140	49	36.75	85.20	7.36	343
24	20	15	10	3	100	49	36.75	85.20	7.35	245
25	20	15	10	5	200	49	36.75	85.20	12.25	490
26	20	15	10	4	170	49	36.75	85.20	9.80	416.50
27	20	15	10	3	140	49	36.75	85.20	7.36	343
28	20	15	10	3	100	49	36.75	85.20	7.35	245
29	20	15	10	5	200	49	36.75	85.20	12.25	490
30	20	15	10	4	170	49	36.75	85.20	9.80	416.50
31	20	15	10	3	140	49	36.75	85.20	7.36	343
32	20	15	10	3	100	49	36.75	85.20	7.35	245

* For the test problems with greater than 32 items, these data are repeated

Table 5.A.3. Resource data of all test problems (monetary value) and their equivalent exergy values (MJ)

Test problem	Resource	Buyer 1	Buyer 1	Buyer 1	Buyer 4	Buyer 5
4 items (real case study)	B_j	840000	830000	820000	810000	800000
	$B_{(x)j}$	4771200	4714400	4657600	4600800	4544000
	F_j	9600	9500	9400	9300	9200
	$\tilde{G}$	(35000, 40000, 60000)				
8 items	B_j	1680000	1660000	1640000	1620000	1600000
	$B_{(x)j}$	9542400	9428800	9315200	9201600	9088000
	F_j	19200	19000	18800	18600	18400
	$\tilde{G}$	(80000, 85000, 105000)				
16 items	B_j	3360000	3320000	3280000	3240000	3200000
	$B_{(x)j}$	19084800	18857600	18630400	18403200	18176000
	F_j	38400	38000	37600	37200	36800
	$\tilde{G}$	(170000, 175000, 195000)				
32 items	B_j	6720000	6640000	6560000	6480000	6400000
	$B_{(x)j}$	38169600	37715200	37260800	36806400	36352000
	F_j	76800	76000	75200	74400	73600
	$\tilde{G}$	(350000, 355000, 375000)				
64 items	B_j	13440000	13280000	13120000	12960000	12800000
	$B_{(x)j}$	176339200	75430400	74521600	73612800	72704000
	F_j	1536000	152000	150400	148800	147200
	$\tilde{G}$	(710000, 715000, 735000)				
128 items	B_j	26880000	26560000	26240000	25920000	25600000
	$B_{(x)j}$	152678400	150860800	149043200	147225600	145408000
	F_j	307200	304000	300800	297600	294400
	$\tilde{G}$	(1430000, 1435000, 1455000)				
256 items	B_j	53760000	53120000	52480000	51840000	51200000
	$B_{(x)j}$	305356800	301721600	298086400	294451200	290816000
	F_j	614400	608000	601600	595200	588800
	$\tilde{G}$	(2870000, 2875000, 2895000)				
512 items	B_j	107520000	106240000	104960000	103680000	102400000
	$B_{(x)j}$	610713600	603443200	596172800	588902400	581632000
	F_j	1228800	1216000	1203200	1190400	1177600
	$\tilde{G}$	(5750000, 5755000, 5775000)				
1024 items	B_j	215040000	212480000	209920000	207360000	204800000
	$B_{(x)j}$	1221427200	1206886400	1192345600	1177804800	1163264000
	F_j	2457600	2432000	2406400	2380800	2355200
	$\tilde{G}$	(115190000, 115195000, 115215000)				

Table 5.A.4. The exergy values of inventory parameters (values in MJ) for 1st item (i=1)

Country		$ee_{Cap(i,s)}$	$ee_{L(i,s)}$	$ee_{Env(i,s)}$	Total
Iran	$A_{(x)i,S}$	34.08	3.56	11.36	49.00
	$A_{(x)ij,b}$	25.56	2.67	8.52	36.75
	$h_{(x)ij}$	8.52	0.89	2.84	12.25
	$C_{(x)i}$	340.80	35.60	113.60	490.00
Afghanistan	$A_{(x)i,S}$	6.6	0.41	2.2	9.21
	$A_{(x)ij,b}$	4.95	0.31	1.65	6.91
	$h_{(x)ij}$	1.65	0.10	0.55	2.30
	$C_{(x)i}$	66.00	4.10	22.00	92.10
Turkey	$A_{(x)i,S}$	123.06	91.36	41.02	255.44
	$A_{(x)ij,b}$	92.29	68.52	30.76	191.58
	$h_{(x)ij}$	30.77	22.84	10.26	63.86
	$C_{(x)i}$	1230.60	913.60	410.20	2554.40
Germany	$A_{(x)i,S}$	18.96	68.25	6.32	93.53
	$A_{(x)ij,b}$	14.22	51.19	4.74	70.15
	$h_{(x)ij}$	4.74	17.06	1.58	23.38
	$C_{(x)i}$	189.60	682.50	63.20	935.30
Canada	$A_{(x)i,S}$	18.78	68.61	6.26	93.65
	$A_{(x)ij,b}$	14.085	51.4575	4.695	70.24
	$h_{(x)ij}$	4.70	17.15	1.57	23.41
	$C_{(x)i}$	187.80	686.10	62.60	936.50

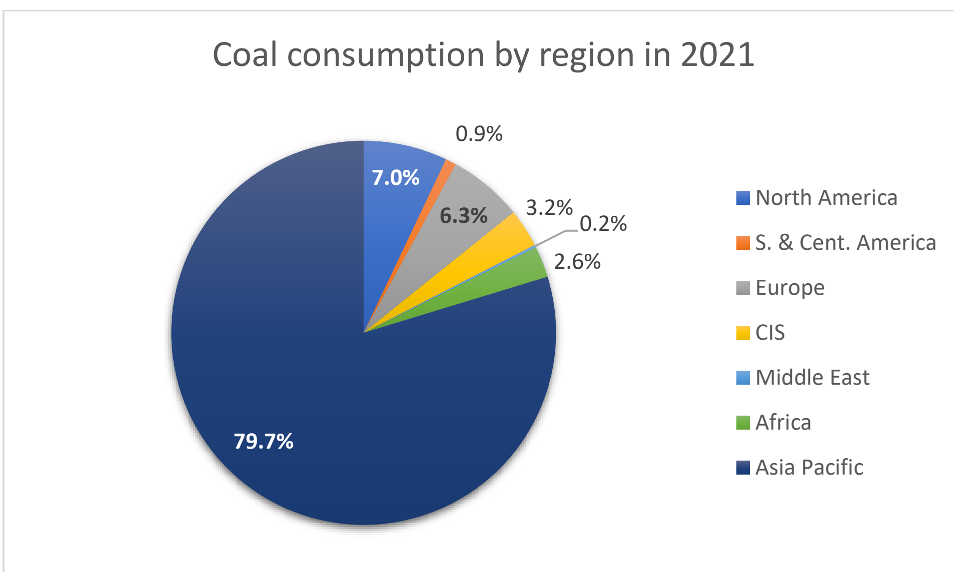

Fig. 5.A.1. Coal consumption by region in 2021

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Assessment of coal supply chain under carbon trade policy by extended exergy accounting method

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Abstract
Within an uncertain environment and following carbon trade policies, this study uses the Extended Exergy Accounting (EEA) method for coal supply chains (SCs) in eight of the world's most significant coal consuming countries. The purpose is to improve the sustainability of coal SCs in terms of Joules rather than money while considering economic, environmental, and social aspects. This model is a multi-product economic production quantity (EPQ) with a single-vendor multi-buyer with shortage as a backorder. Within the SC, there are some real constraints, such as inventory turnover ratio, waste disposal to the environment, carbon dioxide emissions, and available budgets for customers. For optimization purposes, three recent metaheuristic algorithms, including Ant Lion Optimizer, Lion Optimization Algorithm, and Whale Optimization Algorithm, are suggested to determine a near-optimum solution to an "exergy fuzzy nonlinear integer-programming (EFNIP)." Moreover, an exact method (GAMS) is employed to validate the results of the suggested algorithms. Additionally, sensitivity analyses with different percentages of exergy parameters, such as capital, labor, and environmental remediation, are done to gain a deeper understanding of sustainability improvement in coal SCs. The results showed that sustainable coal SC in the USA has the lowest fuzzy total exergy, while Poland and China have the highest.

Keywords Extended exergy accounting (EEA) · Coal supply chain (SC) · Sustainability · Carbon emission · Fuzzy price · Inventory model

1 Introduction

Production systems rely heavily on traditional fossil fuels, mainly coal and oil (Wang et al. 2023). It is estimated that industrial sectors account for over 50% of global energy consumption (Safarian 2023). Almost all coal is composed of dead plant material. As a result of accumulated plant material being buried under anoxic conditions for millions of years,

Extended author information available on the last page of the article

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CHAPTER 6. PAPER FOUR - ASSESSMENT OF COAL SUPPLY CHAIN UNDER CARBON TRADE POLICY BY EXTENDED EXERGY ACCOUNTING METHOD

Forewords

Previous chapter considered carbon tax policy for coal SC. Now, this chapter aims to improve the sustainability of coal SC in both developed and developing countries by incorporating extended exergy accounting and carbon trade policy. Moreover, carbon cap and offset policies will be presented in Chapters 7 and 8, respectively as additional material.

Abstract

Within an uncertain environment and following carbon trade policies, this study uses the Extended Exergy Accounting (EEA) method for coal supply chains (SCs) in eight of the world's most significant coal consuming countries. The purpose is to improve the sustainability of coal SCs in terms of Joules rather than money while considering economic, environmental, and social aspects. This model is a multi-product economic production quantity (EPQ) with a single-vendor multi-buyer with shortage as a backorder. Within the SC, there are some real constraints, such as inventory turnover ratio, waste disposal to the environment, carbon dioxide emissions, and available budgets for customers. For optimization purposes, three recent metaheuristic algorithms, including Ant Lion Optimizer, Lion Optimization Algorithm, and Whale Optimization Algorithm, are suggested to determine a near-optimum solution to an "exergy fuzzy nonlinear integer-programming (EFNIP)." Moreover, an exact method (GAMS) is employed to validate the results of the suggested algorithms. Additionally, sensitivity analyses with different percentages of exergy parameters, such as capital, labor, and environmental remediation, are done to gain a deeper understanding of sustainability improvement in coal SCs. The results showed that sustainable coal SC in the USA has the lowest fuzzy total exergy, while Poland and China have the highest.

Keywords Extended Exergy Accounting (EEA); Coal supply chain (SC); Sustainability; Carbon emission; Fuzzy price; Inventory model

6.1. Introduction

Production systems rely heavily on traditional fossil fuels, mainly coal and oil (Wang et al., 2023). It is estimated that industrial sectors account for over 50% of global energy consumption (Safarian, 2023). Almost all coal is composed of dead plant material. As a result of accumulated plant material being buried under anoxic conditions for millions of years and being exposed to high temperatures and pressures over that time, coal was formed (Australian Government, 2022). Coal is the world's largest source of energy for electricity generation and the production of steel, cement, and paper (U.S. Energy Information Administration (EIA), 2021). About 75% of coal is found in only 5 countries (USA, Russia, Australia, China, and India), while the biggest coal consumers are China (54%), India (18%), USA (6%), Japan (3%), and South Africa (2.3%) (Phengsaart et al., 2023). According to Notes from Poland (2022), Poland ranks 9th in the world in coal consumption to generate 70% of electricity, by far the highest figure in Europe.

In terms of production, China tops the list supplying about 50% of global coal demand. Other key players in the global coal trade include India (9.9%), Indonesia (7.5%), USA (6.4%), Australia (5.9%), Russia (5.3%) and Poland (1.3%) (Phengsaart et al., 2023).

Moreover, coal related SCs represent one of the major concerns for stakeholders (Mehmood et al., 2015) since these industries constitute a significant proportion of carbon dioxide (CO2) emissions (Sun and Yang, 2021). Iron and steel manufacturing, for instance, emitted about 2,600 million tons of carbon in 2019. This number is expected to rise to 2,700 million tons by 2050 if no sustainable development scenario is applied (U.S. Energy Information Administration (EIA), 2022). As society becomes more aware of the value of the environment, waste disposal (imperfect quality items) and carbon dioxide emissions must become leading indicators of coal SC assessment. According to the European Union's Joint Research Centre, China is the largest emitter of CO2 in the world, with 11680 Mt (11.680 GT) of carbon dioxide emissions in 2020. This is just over 32% of the world's total 2020 emissions. The United States and India released the second- and third-highest amount of carbon emissions at 4.535 and 2.411 GT (or roughly 12.6% and 6% of total global emissions). Moreover, Japan and Iran are the 5th and 6th CO2-emitting countries in the world. It should be mentioned that China, the USA, and India are also three of the most populous countries on Earth. In general, developed countries and major emerging markets lead in total carbon dioxide emissions.

Various countries worldwide have set impressive emission-cut goals in the outlook to tackle climate change and the function of sustainable development (Malladi and Sowlati, 2020; Sun and Yang, 2021). In this effort, environmental administrations around the globe agree that pricing carbon emissions is the most inexpensive and successful means to achieve their emission reduction goals (Environment and Climate Change Canada, 2018). The primary carbon pricing strategies are carbon tax, carbon cap, carbon offset, and carbon trade (Malladi and Sowlati, 2020), whereas each approach has different costs and carbon reductions. The benefits of applying each carbon emission policy are not equal for companies involved in coal SC. While some carbon policies are more environmentally friendly, others are more economically beneficial.

Moreover, emerging Industry 4.0 technologies and concerns about global warming show that decision-makers need to change their point of view in assessing the SC's performance (Roozbeh Nia et al., 2020). Shifting from traditional assessment methods to novel and more sustainable methods is one of the critical aspects of the fourth industrial revolution. Extended Exergy Accounting is an innovative method that can help SCs become more sustainable (Aghbashlo et al., 2018). This method integrates the effect of non-energetic manufacturing features into the complete loss assessment (Jawad et al., 2018; Sciubba, 2011). The primary benefit of employing the extended exergy accounting method in the production system is that this method states all outcomes in Joules (instead of dollars); therefore, acceptable assessments among different products can be achieved (Naderi et al., 2021b; Jawad et al., 2018). Moreover, energy (in terms of Joules) is essential to operate all manufacturing and SC processes (Jawad et al., 2015).

It is true that the energy market (natural gas, oil, and coal) today tends to be maturing and unbalanced, characterized by increasing demand and fluctuating supply (Roozbeh Nia et al., 2021). There are tangible signs to verify that demand and price are not predetermined and can influence a broad collection of market influences and customer behaviors. While some scholars have focused on the direct issues, there are also unforeseen issues such as the economic environment, business events, and global politics (Su et al., 2021). For example, oil and gas prices have risen to their highest levels in nearly a decade because of Russia's unprovoked invasion of Ukraine. As a result, many countries have re-evaluated their energy sources. The fact is that uncertainties in demand and energy consumption significantly affect the total SC cost as the penalty cost of unsatisfied demand increases (Priyan et al. 2022). In response to this issue, Zadeh (1965) proposed "fuzzy set theory (FST)," which translates "ill-defined" data into mathematical terms.

Considering these issues, we can present the main research questions of this study as follows:

Q1. Is it possible to assess the sustainability of coal SC under a carbon reduction policy in terms of Joules rather than money to benefit the economy and the environment?

Q2. Generally speaking, coal SC in developing countries, or even China, has the lowest overall cost; however, considering sustainability aspects (social, economic, and environmental characteristics) in Joules, does this assumption still hold true?

Q3. Which country has the most sustainable coal SC in terms of Joules?

Q4. What is the best percentage of exergy components (social, economic, environmental characteristics) to achieve the most significant saving wherever coal SCs are working?

Consequently, the first goal of this study is to find the optimum total exergy of coal SC in different developed and developing countries under carbon trade policy in an uncertain environment (for carbon trade price and customer demand). The second objective is comparing the sustainability of coal SC in eight countries in terms of Joules rather than money. Finally, this research aims to improve the sustainability of coal SC by performing a sensitivity analysis on the three exergy parameters of sustainability (economic, environmental, and social) in the extended exergy accounting method.

Table 6.1. A short review of studies on carbon policies in heavy industries

Author/s (year)	Objective	Results	EEA method	Fuzzy price
Devlin and Yang (2022)	Focused on assessing potential green SCs for an Australia-Japan iron and steel case study	Suggested to reduce the green premium, a carbon tax of A$66–192/t CO2 would be required in 2030 and A$0–70/t CO2 in 2050	No	No
Kunche and Mielczarek (2021)	Presented a comparative overview of studies using the system dynamics approach to evaluate carbon mitigation strategies	This study included their scope, model description, test scenarios, and mitigation methods	No	No
Da et al., (2021)	Examined optimal inputs for clean coal technology in a coal enterprise and optimal carbon reduction quantities in a manufacturer	Focusing on the dominant mode, can affect carbon reduction under different leading models of cap-and-trade with government subsidies	No	No
Hančlová et al., (2020)	Identified and evaluated the interactions between the factors of the EU ETS (prices of emission allowances and grandfathering) and factors of the steel industry such as prices and production levels	Steel companies in the Czech Republic pass on the costs for emissions to their customers	No	No
Li et al., (2020)	Examined the impact of different carbon policies on coal SC networks	The government could guide organizations in reducing carbon by formulating reasonable emission policies	No	No
Da et al., (2019)	Developed a coal-electric power SC strategy that reduces carbon at two levels and operated with financial constraints	The government could encourage a low-carbon economy by controlling bank loan interest rates	No	No
Duan et al., (2019)	Explored the impact of emission reduction policies on China's steel production and economic level	The government should consider the overall and regional balance as well as benchmark values for carbon trading when deciding whether to implement a single or mixed policy	No	No
Gonela (2018)	Designed a hybrid electric SC (HESC) based on coal and biomass for electricity generation in a case study of North Dakota (ND) in the USA	coal-based electricity generation is preferred if the goal is to reduce costs, whereas biomass-based electricity generation is preferred if the goal is to reduce carbon emissions	No	No
Li et al., (2018)	Examined the carbon trading method's consequences in China's power sector	Using a carbon trade policy would negatively affect the entire economy, but the adverse effects would be removed in the future	No	No
Chaabane et al., (2012)	Provided a framework for designing a sustainable SC, in the aluminum industry	Top management will achieve sustainability goals through effective carbon management policies	No	No

6.2. Literature review

The leading publications related to carbon policies in coal-based industries such as cement, steel, etc. are shown in Table 6.1. Based on this table, there is no study that employs the extended exergy accounting method or considers uncertain environment for carbon. Therefore, in this section, the literature related to our study is reviewed in two categories: exergy analysis concepts, and the extended exergy accounting method. After that, research gaps and our contributions in this research compared to existing studies are presented.

6.2.1. Exergy analysis concepts

Although Rant (1956) first introduced the name "exergy," parallel denotations had previously been defined by other researchers. Exergy is the capability to produce work or adequate energy or a quantity of work (Liu et al., 2020). Jaber et al. (2004) tried to connect thermodynamics with inventory management and showed the pertinency of the first and second laws of thermodynamics to manufacture systems through the economic order (production) quantity (EOQ/EPQ) model. Later, Jaber et al. (2006) supposed that the performance of the production systems is like physical systems. Their results showed that the order quantity strategy is to order in more oversized lots less often than when the entropy cost is omitted considering entropy cost. Moreover, Jaber et al. (2009) established Jaber et al. (2004) 's research paper by extending an entropic mathematical model for deciding batch sizes for deteriorating goods. The outcomes of the entropy EOQ model indicated ordering in larger quantities than recommended by the traditional model. Later, Jaber et al. (2011) presented the notion of exergy (valuable energy) cost. The authors added exergy and entropy costs to the EOQ model and established it in a simple reverse logistics system. They supposed forward and backward product streams to be cost-related, and consequently, a revenue method is accepted.

In another study, Jawad and Jaber (2015) proposed using exergy-economics and exergetic costing when developing inventory models. The authors encourage that employing the suggested inventory modeling may be more effective for other sustainable industries. Additionally, Jaber et al. (2017) developed the traditional models of the economical manufacture quantity (EMQ) and Just-in-time (JIT) by comprising other issues. Their outcomes indicated that JIT, which produces items in small quantities more often, experiences lower costs than the EMQ model once associated stress and entropy costs were not counted. Afterward, Jawad et al. (2018) studied the chief issues that can impact the entire cost of an SC, for example, emissions, labor, energy, social effects of shipping, and entropy. The outcomes presented that optimizing the exergetic cost function grows the money significantly to society for a slight extra rise in cost on the section of the SC.

Moreover, in an industrial bread SC in the Netherlands, Banasik et al. (2017a) studied a multi-objective mixed-integer linear programming model to evaluate the collection of eco-efficient solutions relating to manufacturing planning decisions. The authors employed exergy analysis to state environmental performance of the SC. Their outcomes approve the results from the literature that avoidance is the most acceptable waste management policy from an ecological viewpoint. In another study for a mushroom SC, Banasik et al. (2017b) investigated a multi-objective mixed-integer linear programming model to calculate interchanges among financial and ecological gauges and investigate quantitatively substitute recycling tools. The total exergy loss is used in this study as a single metric gauge for environmental performance. They discovered that accepting closing loop tools in modern mushroom manufacture can grow both the overall productivity of the SC and the environmental functioning. Naderi et al. (2021a) presented a mathematical model for enhancing sustainability involving the cost of exergy demolition (entropy) for a coal SC in Iran. The authors employed exergy analysis for a model that involves economic and wasted exergy costs. Their outcomes showed an extra-economic cost, but it will support managers to measure this added cost which is essential for other decisions.

6.2.2. Extended exergy accounting method

It was Sciubba (1998) who developed the traditional analysis of exergy and later introduced the "Extended Exergy Accounting" method (Sciubba, 2003a, 2003b). The extended exergy accounting is expressed as the quantity of the main exergy aggregately exploited to manufacture and discard actual products or services (Song et al., 2019). This method contains energy and material's main aggregate exergy subject and cost corresponding to economic externality (labor and capital) and ecological externality (environmental remediation). The extended exergy accounting connects production systems' processes with surrounding systems (Song et al., 2019). Regarding the method, to the best of the authors' knowledge, only three studies employed this method for inventory management or SC. For example, Jawad et al. (2015) employed the notions of the extended exergy accounting method in inventory management for three factories in the USA, China, and Germany to involve the three aspects of sustainability: financial, ecological, and social. The outcomes presented that the order quantity in the companies is different since the corresponding exergy of money, labor and environment costs are not the same in each company. Later, Jawad et al. (2016) extended the traditional EPQ model by employing the extended exergy accounting method and thermodynamics laws to determine the degree of sustainability of a manufacture-inventory model. The outcomes revealed that an item's cost has a crucial function in diminishing the model's entropy creation (exergy lost). Moreover, for a conventional cement production SC in China, Song et al. (2019) utilized the extended exergy accounting method to estimate the cumulative exergy consumption (CExC), labor and money exergy, and ecological remediation exergy. They measured cement manufacture's environmental costs and the segments with exergy deficiencies. Finally, Naderi et al. (2021b) studied the utilized exergy for a sustainable SC through an extended exergy accounting method for a food SC in Iran. They suggested a hybrid global- and local-search metaheuristic algorithm to solve the model. Their findings revealed that exergy minimization substantially reduces the cost for society as different from raising the cost in some sections of the SC. For example, the recommended method delivers 4.48% savings in the utilized exergy of the SC through undertaking added economic costs.

To explore more about exergy components, exergy analysis and the extended exergy accounting method in detail, we suggest Arango-Miranda et al. (2018), Dincer and Rosen (2013), and Ehyaei et al. (2019) to interested readers. Additionally, a brief review of papers that used exergy analysis and the extended exergy accounting method (comparing with our proposed model) is available in Table 6.2. Based on this table, for example, no study considers carbon policy with the extended exergy accounting method.

Table 6.2. A brief review of research works in exergy analysis of supply chain

Authors (years)	**Objective**	**Single objective /multi**	**Solving methods**	**Verification**	**Compare SCs**	**Inventory model**	**EEA technique**	**Carbon policy**	**Inventory turnover**	**Balanced budgeting**	**Waste discarding**	**Fuzzy**	**Shortage**	**VMI policy**	**Multi-buyer**
Naderi et al. (2021a)	Provide a mathematical model for improving coal SC sustainability while minimizing the cost of exergy destruction (entropy) in SC	Single	Metaheuristic algorithm	No	No	No	No	No	No	No	No	No	No	No	Yes
Naderi et al. (2021b)	Provide an exergy analysis to model and minimize the consumed exergy for sustainable SC	Single	Metaheuristic algorithm	Branch & bound	No	No	Yes	No	No	No	No	No	No	No	Yes
Jawad et al. (2018)	Minimize the total cost of the developed SC model while focusing on the pillars of sustainable developments.	Single	Exact method	N/A	No	Yes	No	No	No	No	No	No	No	No	No
Banasik et al. (2017a)	Develop a mathematical model for quantitative assessment of alternative production options that are associated with different ways to deal with waste in food SCs	Multi	Exact method	N/A	No	No	No	No	No	No	Yes	No	No	No	No
Banasik et al. (2017b)	Quantify trade-offs between economic and environmental indicators and explore quantitatively alternative recycling technologies	Multi	Exact method	N/A	No	No	No	No	No	No	No	No	No	No	Yes
Jawad et al. (2016)	Re-examines the economic production quantity (EPQ) model to reflect sustainability needs by using EEA and the laws of thermodynamics.	Single	Exact method (EPQ formula)	N/A	N/A	Yes	Yes	No	No	No	No	No	No	No	No

Jawad et al. (2015)	Use an exergy model to determine the EOQ inventory policies for three firms operating in the USA, Germany, and China.	Single	Exact method (EOQ formula)	N/A	N/A	Yes	Yes	No	No	No	No	No	No	No	No
Santhi and Karthikeyan (2015)	Determine the cycle length and the replenishment order quantity of an EOQ model to maximize the profit.	Single	Exact method (EOQ formula)	N/A	N/A	Yes	No	No	No	No	No	Yes	No	No	No
Jawad and Jaber (2015)	Use exergo-economics and exergetic costing when developing inventory models	Single	Exact method	N/A	N/A	Yes	No	No	No	No	No	No	No	No	No
Jaber and Jawad (2015)	Estimate the entropy created in EPQ and JIT systems	Single	Exact method (EPQ formula)	N/A	N/A	Yes	No	No	No	No	No	No	No	No	No
Jaber et al. (2009)	A mathematical model to determine batch sizes for deteriorating items while minimizing the entropy of the EOQ model.	Single	Exact method (EOQ formula)	N/A	N/A	Yes	No	No	No	No	No	No	No	No	No
Jaber and Rosen (2008)	Improve production system performance by applying thermodynamics' first and second laws to reduce system entropy (or disorder).	Single	Exact method (EOQ formula)	N/A	No	Yes	No	No	No	No	No	No	No	No	No
Jaber (2007)	Estimate the hidden costs of the EOQ model by applying the first and second laws of thermodynamics to reduce system entropy (or disorder) at a cost.	Single	Exact method (EOQ formula)	N/A	N/A	Yes	No	No	No	No	No	No	No	No	No
Proposed model	Optimize the fuzzy exergy cost of an SC with the EEA method under trade emission policy	Single	Metaheuristic algorithm	GAMS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

6.2.3. Research gaps and our contributions

Regarding literature review, Tables 6.1 and 6.2, there are still several research gaps, including G1. There is a lack of research that assess a SC under carbon policy within an uncertain environment, for example, fuzzy carbon price or customer demand. G2. It is rare to find studies that assess a SC in terms of Joules instead of money (as traditional performance measures) and simultaneously evaluate all sustainability aspects, such as economic, labour, and environmental. G3. There is a lack of examinations that employ the extended exergy accounting method to assess a SC under any carbon reduction policy. As a matter of fact, no exergy analysis method in the literature takes into consideration carbon emission policy. G4. There is a scarcity of studies that compare the sustainability of coal SCs between developed and developing countries under carbon trade policy with the extended exergy accounting method. G5. There is a deficiency of investigation to find the best percentage of exergy components (social, economic, environmental aspects) in the extended exergy accounting method for a SC. G6. In addition, some real-world issues are ignored, such as considering the inventory turnover ratio for SC models, defective quality products discarded into the environment, shipping charges on the whole of coal SC (mining, railway transportation and steel making), vendor managed inventory (VMI) policy for coordinating SC, and the costs of loan/investment for budget limitation. In brief, the three contributions of this study to the literature are as follows:

- Improving the sustainability of coal SCs in terms of Joules (total exergy rather than traditional monetary objectives) in developed and developing countries under carbon trade policy and the uncertain environment by employing the extended exergy accounting method.
- Comparing the sustainability of coal SC in eight countries to determine which country has the most sustainable coal SC in terms of Joules.
- Finding the best value of exergy components (social, economic, environmental characteristics) for coal SC in both developed and developing countries which creates the highest sustainability.

The remainder of the study is structured as follows. In Section 6.3, the problem is outlined, the suppositions are stated, and the problem is mathematically expressed into a fuzzy nonlinear integer-programming model under emission trade policy. In Section 6.4, exergy modeling of fuzzy optimization using extended exergy accounting is presented. The proposed solution method is presented in Section 6.5 to solve the problem. Section 6.6 presents computational test problems and sensitivity analysis of exergy values to reveal the recommended solution methods' relevance. Finally, conclusions and potential studies are offered in Section 6.7.

6.3. Problem description and model formulation

6.3.1. Problem description

Elevated energy market uncertainties (e.g., price and demand), disruptions (e.g., COVID-19 and global warming), and competition (e.g., global market and customer satisfaction) over current years have produced variations (negative and positive) to coal SC administration (Teerasoponpong and Sopadang, 2022). It is true that coal is a low-cost and plentiful resource, but carbon dioxide (CO2) from coal usage in industries such as power plant, cement, steel and paper is responsible for about 40% of global greenhouse gas (GHG) emissions. Therefore, it is the responsibility of legislations and coal SC decision making to invest and innovate for cutting their carbon emissions.

This paper is inspired by the studies of Jawad et al. (2016) and Naderi et al. (2021a) and uses them to develop a multi-product multi-limitation EPQ model with backorder for a coal SC in eight countries under the fuzzy environment. Moreover, a VMI contract is employed for a single supplier and multi-buyer to coordinate the coal SC. The extended exergy accounting method with Mega-Joules (MJ) as a universal unit of measure is used to find the total exergy of the model. Besides, the buyers' demand, purchasing price per unit of product, cost of goods sold per unit of product, and carbon price of each unit of carbon are considered fuzzy. A famous carbon reduction policy, called carbon trade, is used to compare the model's performance as a sustainability measure and control the produced carbon emission of SC enterprises. Moreover, three recent metaheuristic algorithms are exercised to obtain a near-optimum solution of the developed exergy fuzzy nonlinear integer programming (EFNIP) to diminish the fuzzy total exergy of a coal SC. Additionally, ten numerical examples, including an actual case study in coal SC in Iran, were presented to display the pertinency of the proposed model. Likewise, the results are compared with the exact method (GAMS) to confirm the outcomes. Finally, a sensitivity analysis with changing the percentage of exergy parameters, including the capital, labor, and environmental remediation, has been done with seven different exergy sets of percentages (A-G) in eight developed and developing countries. Sensitivity analysis aims to find the best exergy values (capital, labour, and environmental remediation) of the extended exergy accounting method that create the highest sustainability for coal SC of Iran, Australia, China, India, Japan, Poland, the USA, and Zimbabwe.

6.3.2. Assumptions

Considering the purpose of this research to develop the sustainability of coal SC by integrating carbon trade policy and the extended exergy accounting method, we consider the succeeding assumptions for the mathematical preparation. More sophisticated assumptions are considered for future research in Section 6.7. There is a single supplier, multi-buyer coal SC with n products (different grades of coal) when stockout is permitted in the type of backorder for all products. The supplier's production rate for all products is fixed and known (EPQ model). In this model, quantity discount is not permitted, and the supplier pays the shipping cost whereas the setup and keeping costs are known. There are constraints on the capacity of the buyer's warehouse, budget and order quantity of a product and the total number of orderings. Additionally, all transportation between supplier and buyers are done by the railway system when distance between them is fixed and known. Moreover,

(a) Buyer's demand for the entire product, the price for all products and the price of carbon trade are fuzzy (trapezoidal fuzzy number)

(b) The linear backorder cost per unit per time unit is known for the entire products while the time-independent fixed backorder cost per unit is supposed to be zero

(c) Orders are supposed to be immediate (lead time=0)

(d) Coal Mining (supplier), shipping, and utilizing coal in the steel companies (buyers) produce carbon emission and waste (defective quality products) disposal to the environment.

6.3.3. Notations

The indices, factors, and decision variables of the SC model are described in Table 6.3.

The following subsections will develop a non-exergy mathematical model (a basic model) of the coal SC for carbon trade policy (subsection 6.3.4). Then it has converted to a fuzzy model in subsection 6.3.5.

Table 6.3. Notations

Indices:	
i: Index of the products; $(i = 1,2,\ldots,n)$	j: Index of buyers; $(j = 1,2,\ldots,m)$
Factors: D_{ij}: Demand rate of product i for buyer j P_i: Rate of production of the i^{th} product ($P_i \geq \sum_{j=1}^{m} D_{ij}$) Q_{Max}: Upper limit of transportation capacity on each order quantity N_{Max}: Max. total number of orders by all buyers C_i: Buying price per unit of product i by buyers C_o: Cost of goods sold per unit of product i by the supplier ITR_j: Inventory turnover ratio of buyer j C_{trade}: Emission trade price of each unit of produced carbon X_j: Total available budget of all products for buyer j int^-: The interest rate of the essential loan for buyer j int^+: Interest (benefit) rate of new investment for buyer j $K_{i,s}$: Supplier's fixed setup cost per unit of product i $K_{ij,b}$: Constant ordering cost per unit of product i for buyer j δ_m: Proportion of imperfect quality items in mine process δ_t: Proportion of imperfect quality items in the transportation process δ_k: Proportion of imperfect quality items in steel manufacturer	t_f: Constant shipping cost of each order which is paid by the supplier (VMI contract) t_v: Variable shipping cost per unit of a product which is paid by the supplier (VMI contract) t_L: Labor cost for loading/unloading of coal per hour t_M: Machine/equipment cost for loading/unloading of coal Lo: Loading time of coal in a railcar (railway wagon) Un: Unloading time of coal from a railcar h_{ij}: Keeping cost per unit of product i held in the warehouse of buyer j in a period s_1: fixed backorder cost per unit (time-independent) s_2: Linear backorder cost per unit per time unit W_j: Available storage area of buyer j for all products L_j: Distance between supplier and buyer j (km) θ_m: Emissions factor of mining (ton/unit) θ_t: Emissions factor of shipping (ton/unit) θ_k: Emissions factor of furnace in steel manufacturer (ton/unit) E_j: Upper limit on aggregate carbon emissions of all products of each buyer F: Upper limit on total imperfect quality items disposal to the environment by all processes
Decision variables: Q_{ij}: Order quantity of product i for buyer j b_{ij}: Maximum backorder level of product i for buyer j in a cycle x_j^+: Total new investment for buyer j x_j^-: Total required loan for buyer j	 e_j^+: Emission credits that should be bought by buyer j e_j^-: Emission credits that could be sold by buyer j

6.3.4. A non-exergy modeling of coal SC under carbon trade policy

6.3.4.1. Objective function

Carbon trade integrates government regulations and market methods in a flexible policy that the Kyoto Protocol plans. With this policy, companies' carbon emissions are restricted (see Eq. 9); consequently, if a company generates carbon dioxide further than the launched cap, it must purchase extra carbon credits (e^+). In contrast, the company could sell its carbon credits (e^-) to other companies on the carbon market (Jiang et al., 2016), whereas the carbon price (C_{trade}) is determined by supply and demand in this market (Li et al., 2020). Although the price of carbon is considered known and fixed in the literature, this study considers it fuzzy (see subsection 6.3.5). The trading strategy provides businesses with a great motivation to save money by reducing emissions in the most economical methods. This policy is employed in the European Union, Quebec province in Canada, California in the United States of America, and seven areas in China (Haites 2018). Consequently, the carbon trade cost is

$$Z_1 = \sum_{j}^{m} C_{trade} \times \left(e_j^+ - e_j^-\right) \tag{6.1}$$

The shipping costs accounted for about 40% of the entire delivered cost of coal in 2019 (U.S. Energy Information Administration (EIA), 2019). Transportation costs are also impacted by road distance, accessibility of shipping mode and supply source alternatives, and the competition among coal and other goods for shipping. Therefore, the total transportation cost of coal includes constant (t_f) and variable (t_v) costs, along with the cost of loading/unloading coal (t_L) in/from railcars and cost of equipment (t_M) is

$$Z_2 = \sum_{i}^{n}\sum_{j}^{m}\left[\left(\frac{D_{ij}}{Q_{ij}}.t_f\right) + \left(Q_{ij}.t_v\right) + \left(\frac{D_{ij}}{Q_{ij}}.(Lo + Un).(t_L + t_M)\right)\right] \tag{6.2}$$

Where (Lo, Un) are the loading/unloading time of coal in/from a railcar. The vendor-managed inventory (VMI) strategy is the regular inventory management in SC in which the upstream company completely controls the inventory at the downstream company's location (Giovanni, 2021). In the VMI system, the determinations about scheduling and amount of buyer's replenishment are decided by the supplier that is assumed to have comprehensive information concerning the customers' requirements, to prevent stockouts (Çomez-Dolgan et al., 2021, Maio and Lagana, 2020). Therefore, it is expected that the supplier gives the ordering, shipping, and keeping costs rather than the buyer as a part of the stated contract; the buyer gives no cost (Mateen et al., 2014; Yao et al., 2007; Razmi et al., 2010; Pasandideh et al., 2011; Roozbeh Nia et al., 2014, 2015). Furthermore, in an EPQ model with defective quality items and stockout as a backorder that utilizes the VMI strategy, the coal SC's total inventory cost is established by calculating the ordering/setup ($TC_{O_{ij}}$), keeping ($TC_{H_{ij}}$), stockout ($TC_{S_{ij}}$), and purchasing ($TC_{P_{ij}}$) costs as (Pasandideh et al., 2010, 2011)

$$Z_3 = TC_{O_{ij}} + TC_{H_{ij}} + TC_{S_{ij}} + TC_{P_{ij}} \tag{6.3}$$

Where,

$$TC_{O_{ij}} = \sum_{i}^{n}\sum_{j}^{m}\frac{D_{ij}}{Q_{ij}}\left(K_{i,s} + K_{ij,b}\right) \tag{6.4}$$

$$TC_{H_{ij}} = \sum_{i}^{n}\sum_{j}^{m}\frac{h_{ij}}{2Q_{ij}\left(1-\frac{D_{ij}}{P_i}\right)}\left(Q_{ij}(1-\delta_m)\left(1-\frac{D_{ij}}{P_i}\right) - b_{ij}\right)^2 \tag{6.5}$$

$$TC_{S_{ij}} = \sum_{i}^{n}\sum_{j}^{m}\left(\frac{s_1.b_{ij}^2}{2Q_{ij}\left(1-\frac{D_{ij}}{P_i}\right)} + \frac{s_2.b_{ij}.D_{ij}}{Q_{ij}\left(1-\frac{D_{ij}}{P_i}\right)}\right) \tag{6.6}$$

$$TC_{P_{ij}} = \sum_{i}^{n}\sum_{j}^{m} C_i.D_{ij} \tag{6.7}$$

Where (D_{ij}, Q_{ij}, h_{ij}) are the demand rate, order quantity and holding cost per unit of coal i for buyer j, respectively. As mentioned previously, the existing budget of each buyer could be deposited in a bank account or invested in other projects to get profits. Now, we take into account a real-world balanced limitation (see subsection 6.3.4.2) where the total amount of the existing budget for each buyer is restricted (see Eq. 6.8). To the best of the authors' knowledge, this type of objective function and limitation, have not been studied yet. On the one hand, each buyer's under-achievement budget (x_j^+ as a decision variable) is regarded as the benefit. It means this amount of money (x_j^+) may be invested in a new project with an actual interest rate (int^+) and make a profit (as a $int^+ \times x_j^+$) for the buyer. On the other hand, the over-achievement budget (x_j^- as a decision variable) is regarded as the cost. It means the buyer must get a loan with the amount of (x_j^-) and an interest rate of (int^-). After All, the buyer should pay this loan as well as the interest rate ($x_j^- + [int^- \times x_j^-]$) at the end of the period. Therefore, the total cost/benefit associated with the budget of all buyers is

$$Z_4 = \sum_{j}^{m}\left[x_j^- + \left(int^- \times x_j^-\right) - \left(int^+ \times x_j^+\right)\right] \tag{6.8}$$

Wherever in Eq. (6.8), the first two components are linked to the cost functions, and the last part with a negative symbol is related to the benefit obtained. Moreover, under and over-achievement budgets (x_j^+, x_j^-) are not known parameters and are considered decision variables. Hence, the non-exergy total cost of coal SC under the carbon trade policy is the summation of $TC_{trade} = Z_1 + Z_2 + Z_3 + Z_4$.

6.3.4.2. The constraints

The constraints of this model are as follows:

$$\frac{\sum_i^n \sum_j^m C_0 \,. D_{ij}}{\sum_i^n \sum_j^m \frac{C_0 . \left(Q_{ij}(1-\delta_m)\left(1-\frac{D_{ij}}{P_i}\right)-b_{ij}\right)^2}{2Q_{ij}\left(1-\frac{D_{ij}}{P_i}\right)}} \geq ITR_{\,j} \tag{6.9}$$

$$\sum_i^n \left[\left(Q_{ij}.\theta_m\right) + \left(\frac{D_{ij}}{Q_{ij}}.L_j.\theta_t\right) + \left(Q_{ij}.D_{ij}.\theta_k\right) \right] + \left(e_j^- - e_j^+\right) = E_j \tag{6.10}$$

$$\sum_i^n \sum_j^m \left[\left(Q_{ij}.\delta_m\right) + \left(Q_{ij}.(1-\delta_m).\delta_t\right) + \left(Q_{ij}(1-\delta_m).(1-\delta_t).\delta_k\right) \right] \leq F \tag{6.11}$$

$$\sum_i^n \left[Q_{ij}(1-\delta_m)\left(1-\frac{D_{ij}}{P_i}\right) - b_{ij} \right] \leq W_j \tag{6.12}$$

$$\sum_i^n \left[C_i.Q_{ij}(1-\delta_m) \right] + \left(x_j^+ - x_j^-\right) = X_j \tag{6.13}$$

$$\sum_i^n \sum_j^m \frac{D_{ij}}{Q_{ij}} \leq N_{Max} \tag{6.14}$$

$$Q_{ij} \leq Q_{Max} \tag{6.15}$$

$$b_{ij} \leq Q_{ij} \tag{6.16}$$

Eq. (6.9) is an inventory turnover ratio ($ITR_{\,j}$) limitation. To the best of the authors' knowledge, this limitation has not been presented in SC literature before. The inventory turnover ratio is applied as a comparative measure of inventory performance between competitors and is crucial to control inventory (Beklari et al., 2018). This proportion is an economic index that merges the cost of goods sold with average inventories at cost (Kwak 2019). The inventory turnover ratio shows how often inventories are turned over a period. For Eq. (6.10), as mentioned before, with the policy of carbon trade, each buyer inside coal SC can only produce within an offered cap (E_j) of emission. If this actual emission amount goes above the emission limit, the company must purchase carbon credits (e^+). The company can vend these extra emission credits (e^-) if the actual emission amount runs under the emission limit (Li et al., 2020). Hence, with the emission trade policy, a new emission restriction is included in the model where Eq. (6.10) corresponds to the total generated carbon in mining, shipping, and steelmaking processes. In Eq. (6.10), ($\theta_m, \theta_t, \theta_k$) are emissions factors in mining, transportation, and steel manufacturer processes, respectively. Additionally, L_j is the distance between the coal vendor and buyer j. Eq. (6.11) aims to make the model green since it considers a limitation (F) on total defective products (waste) disposal to the environment by all processes in coal SC. In this equation, ($\delta_m, \delta_t, \delta_k$) are the proportions of imperfect quality items in mining, transportation, and steel manufacturer processes, respectively. Furthermore, Eq. (6.12) expresses that the warehouse space of each buyer (W_j) is restricted, where (b_{ij}) is the backorder amount of coal i for buyer j in a cycle (a decision variable).

As shown before, a real-world contractual agreement grants balanced constraints (Eq. 6.13) for the existing budget of each buyer (X_j). To the best of the authors' knowledge, this type of limitation has not been given in SC literature in the past. Where Eq. (6.13) indicates that, on the one hand, if the total paid-out money of a buyer is below the existing budget ($\sum_i^n C_i . Q_{ij}(1-\delta_m) < X_j$), the buyer saves an amount of ($x_j^+ > 0$). It is possible the company invests this amount in a new project and makes a profit (see Eq. 6.8). On the other hand, if the total paid out money of a buyer is more than the existing budget ($\sum_i^n C_i . Q_{ij}(1-\delta_m) > X_j$), so the buyer demands to get a loan with the amount of ($x_j^- > 0$). The total cost/benefit linked to this balanced limitation is expressed in Eq. (6.8). In addition, Eq. (6.14) is related to the limitation on the total number of orders (N_{Max}) by all buyers. Additionally, there is a constraint for the shipping system (railway) while the Max. of shipping capacity (Q_{Max}) for each order quantity is stated in Eq. (6.15). Finally, based on Eq. (6.16), the quantity of backorder of product i for j^{th} buyer (b_{ij}) in a cycle should be fewer than or equal to its order amount (Q_{ij}). It should be mentioned that intending to simplify the mathematical model; we ignore the cost of purchasing (Eq. 6.7) in our model. Regarding Eqs. (6.1)-(6.16) and under carbon trade policy, the non-exergy crisp model of “multi-product” balanced limitations single-vendor multi-buyer (SVMB) EPQ can be easily achieved as

$$TC_{trade} = \sum_i^n \sum_j^m \left[\frac{D_{ij}}{Q_{ij}}\left(K_{i,s} + K_{ij,b}\right) + \frac{h_{ij}}{2Q_{ij}\left(1-\frac{D_{ij}}{P_i}\right)}\left(Q_{ij}(1-\delta_m)\left(1-\frac{D_{ij}}{P_i}\right) - b_{ij}\right)^2 + \left(\frac{s_1 . b_{ij}^2}{2Q_{ij}\left(1-\frac{D_{ij}}{P_i}\right)} + \frac{s_2 . b_{ij} . D_{ij}}{Q_{ij}\left(1-\frac{D_{ij}}{P_i}\right)}\right)\right] + \sum_j^m C_{trade} \times \left(e_j^+ - e_j^-\right)$$

$$+ \sum_j^m \left[x_j^- + \left(int^- \times x_j^-\right) - \left(int^+ \times x_j^+\right)\right] + \sum_i^n \sum_j^m \left[\left(\frac{D_{ij}}{Q_{ij}} . t_f\right) + \left(Q_{ij} . t_v\right) + \left(\frac{D_{ij}}{Q_{ij}} . (Lo + Un) . (t_L + t_M)\right)\right]$$

$s.t.$

$$\frac{\sum_i^n \sum_j^m C_0 . D_{ij}}{\sum_i^n \sum_j^m \frac{C_0 . \left(Q_{ij}(1-\delta_m)\left(1-\frac{D_{ij}}{P_i}\right) - b_{ij}\right)^2}{2Q_{ij}\left(1-\frac{D_{ij}}{P_i}\right)}} \geq ITR_j$$

$$\sum_i^n \left[\left(Q_{ij} . \theta_m\right) + \left(\frac{D_{ij}}{Q_{ij}} . L_j . \theta_t\right) + \left(Q_{ij} . D_{ij} . \theta_k\right)\right] + \left(e_j^- - e_j^+\right) = E_j$$

$$\sum_{i}^{n}\sum_{j}^{m}\left[\left(Q_{ij}.\delta_m\right)+\left(Q_{ij}.(1-\delta_m).\delta_t\right)+\left(Q_{ij}(1-\delta_m).(1-\delta_t).\delta_k\right)\right]\leq F$$

$$\sum_{i}^{n}\left(Q_{ij}(1-\delta_m)\left(1-\frac{D_{ij}}{P_i}\right)-b_{ij}\right)\leq W_j$$

$$\sum_{i}^{n}C_i.Q_{ij}(1-\delta_m)+\left(x_j^{+}-x_j^{-}\right)=X_j$$

$$\sum_{i}^{n}\sum_{j}^{m}\frac{D_{ij}}{Q_{ij}}\leq N_{Max}$$

$$Q_{ij}\leq Q_{Max}$$

$$b_{ij}\leq Q_{ij}$$

$$Q_{ij}>0, integer, i=1,2,\dots,n$$

$$b_{ij}\geq 0, integer, j=1,2,\dots,m$$

$$x_j^{+},x_j^{-},e_j^{+},e_j^{-}\geq 0, \quad (6.17)$$

In this non-exergy sustainable model, we are looking to optimize four objectives simultaneously: (a) the total inventory cost, (b) the entire cost associated with the additional required budget of all buyers, (c) the total coal transportation cost among SC members, (d) and the cost of produced carbon emission by all processes. Consequently, we have six decision variables, for example, the amount of required loan/investment for each buyer (x_j^{-}, x_j^{+}), the carbon credits for each buyer (e_j^{+}, e_j^{-}), the order quantity of each item for each buyer (Q_{ij}), and the amount of backorder of each item for each buyer (b_{ij}). The following subsection considers uncertainty to the non-exergy model in Eq. (6.17).

6.3.5. The inventory model in fuzzy environment

Stochastic modelling methods can solve the inventory model with sufficient historical data for ambiguous parameters (Aka and Akyüz, 2021). Despite this, it is problematic to have actual and exact random distributions because of the unavailability of historical data on the coal SC in Iran. Moreover, in the real coal SC business world, the market environments are full of ambiguities in a non-stochastic sense (Panja and Mondal, 2019). Therefore, most inventory models in the literature consider an impractical assumption; all the inventory settings occur in a deterministic and particular condition. To cope with this unrealistic assumption, Zadeh (1965) proposed "fuzzy set theory (FST)," which converts "ill-defined" data to mathematical terminologies. Accordingly, the problem considered in this study is a fuzzy EPQ SVMB multi-product SC. As discussed in Hanss (2005), different types of fuzzy numbers exist, for example, triangular, trapezoidal, and Gaussian fuzzy numbers. Trapezoidal numbers are usually used to express ambiguous or uncertain information since they can deal with the ambiguity or uncertainty of complex fuzzy information

(Wan et al., 2021). Moreover, the trapezoidal fuzzy number is a commonly used representation of uncertain information in real applications (He et al., 2018). Therefore, in this study, the buyer's demands, the unit price of products, the cost of goods sold per unit of product, and the carbon trade price are considered ill-defined and trapezoidal fuzzy numbers.

6.3.5.1. Graded Mean Integration representation technique

To figure out and employ the consequent responses from fuzzy SC, the results should be relevant for the top management of the companies. Therefore, defuzzification is necessary (Shekarian et al., 2017). As several techniques for the defuzzification of fuzzy numbers can be applied, one of the most employed, the "graded mean integration" technique (Chen and Hseih, 1998), is used in this paper. In most circumstances employing the extension rule to get the membership function of the fuzzy total cost function is not easy. Because the membership function does not alter with fuzzy arithmetic procedures, it is probable to estimate the defuzzified amount immediately through the graded mean integration technique through arithmetic procedures (Mahata and Goswami, 2013). Chen and Hseih (1998) method is helpful since it scores each point of support set of fuzzy numbers, and it is probable to determine the level of resemblance among fuzzy numbers concerning graded mean integration amounts. Suppose $\tilde{A} = (a_1, a_2, a_3, a_4)$ is a trapezoidal fuzzy number and L^{-1} , R^{-1} are correspondingly the inverse functions of L and R. Describe the graded mean h-level amount of $\tilde{A}$ as $\frac{h[L^{-1}(h)+R^{-1}(h)]}{2}$ (Mahata and Goswami, 2013). So, the graded mean integration description of fuzzy number $\tilde{A}$ can be calculated as

$$P(\tilde{A}) = \frac{\int_0^1 \frac{h[L^{-1}(h)+R^{-1}(h)]}{2} dh}{\int_0^1 h.dh} = \int_0^1 h[L^{-1}(h) + R^{-1}(h)].dh \tag{6.18}$$

For trapezoidal fuzzy number $\tilde{A} = (a_1, a_2, a_3, a_4)$, $L^{-1}(h) = a_1 + (a_2 - a_1)h$ and $R^{-1}(h) = a_4 + (a_4 - a_3)h$. Afterward, the graded mean integration depiction of trapezoidal fuzzy number $\tilde{A} = (a_1, a_2, a_3, a_4)$ by Eq. (6.18) is given by

$$P(\tilde{A}) = \frac{a_1+2a_2+2a_3+a_4}{6} \tag{6.19}$$

Therefore, in this study the buyers' demand ($\widetilde{D_{ij}}$), purchasing price per unit of product i ($\tilde{C_i}$), cost of goods sold per unit of product i ($\widetilde{C_0}$), and trade price of each unit of carbon ($\widetilde{C_{trade}}$) are considered trapezoidal fuzzy numbers i.e. $\widetilde{D_{ij}} = \left(D_{ij,1}, D_{ij,2}, D_{ij,3}, D_{ij,4}\right)$, $\tilde{C_i} = \left(C_{i,1}, C_{i,2}, C_{i,3}, C_{i,4}\right)$, $\tilde{C_0} = \left(C_{0,1}, C_{0,2}, C_{0,3}, C_{0,4}\right)$, and $\widetilde{C_{trade}} = \left(C_{t,1}, C_{t,2}, C_{t,3}, C_{t,4}\right)$.

6.4. Exergy modeling of fuzzy optimization of multi-buyer coal SC

The earlier section presents a fuzzy monetary sustainable EPQ model (minimum Dollar or Euro) for a coal SC under a carbon trade policy. In this section, we consider three factors of hidden cost in a coal SC such as capital (*Cap*), labor (*L*), and environment (*Env.*) remediation by employing the extended exergy accounting method and then convert the monetary model (Eq. 6.17) to the equivalent exergy model.

6.4.1. Extended exergy accounting

Extended exergy accounting is the quantity of initial exergy (in Joules; J) aggregate consumed in the manufacture, operation, and discarding procedure of certain goods or services. This method delivers more information than an entirely financial method, which cannot support any suggestion about utilizing global resources (Jawad et al., 2016). The initial aggregate exergy includes material (*M*), and energy (*E*), corresponding exergy of labor (*L*), money (*Cap.*), and ecological (*Env.*) remediation costs, of which the last three components are counted as the cost correspondence of economic externality and ecological externality (Song et al., 2019). It can be expressed as (Naderi et al., 2021b)

$$EEA = ee_M + ee_E + ee_{Cap} + ee_L + ee_{Env} \tag{6.20}$$

Where $(ee_M + ee_E)$ are the exergy of raw materials and energy flows, used in producing a product. The summation of these two exergies $(ee_M + ee_E)$ could be determined by transforming the summation of purchasing costs $(\sum_i^n \sum_j^m C_i D_{ij})$ in the inventory model to the exergy equivalents (Jawad et al., 2015). As mentioned in subsection 6.3.4.2, for simplifying the mathematical model, we ignore the purchasing costs (and therefore exergy equivalents: $ee_M + ee_E$) since it does not affect the model's order quantity (Q_{ij} as decision variable). All related costs should be transformed into comparable exergetic amounts to employ the extended exergy accounting method in an inventory model. The setup (*K*), buying (*C*), and keeping (*h*) costs can be categorized into the summation of three exergetic amounts of capital, labor, and environment $\left(ee_{Cap,i} + ee_{L,i} + ee_{Env,i}\right)$, respectively (Jawad et al. 2018),

$$ee_{Cap,i} = \left(i_{Cap}\right) \times ee_{Cap} \tag{6.21}$$

$$ee_{L,i} = i_L \times ee_L / Labor\ cost \tag{6.22}$$

$$ee_{Env,i} = i_{Env} \times ee_{Env} \tag{6.23}$$

where $i = K, C, or\ h$ are calculated in J/order, J/unit, and J/unit/year, respectively. Concerning Eq. (6.23) for the exergy of environment characteristic, we accept the approach of Chen and Chen (2009), who respected $(ee_{Env} = ee_{Cap})$. Consequently, Eq. (6.23) is switched to $(ee_{Env,i} = i_{Env} \times ee_{Cap})$. It comprises any cost paid to get labor, capital, material, and other items used to reduce the damaging environmental effect of manufacturing a product, operating a SC, or delivering some other service (Jawad et al., 2015). Moreover (Jawad et al., 2015, 2018; Sciubba, 2011; Naderi et al., 2021b),

$$ee_{Cap} = \alpha.\beta\left(\frac{Ex_{in}}{M_2}\right) \tag{6.24}$$

$$ee_L = \frac{\alpha.Ex_{in}}{(NWH)_{total}} \tag{6.25}$$

Where (ee_{Cap}, ee_L) are the specific exergy equivalent of one monetary unit (€, \$, £, ¥) and the unit equivalent exergy of labor, respectively. Additionally, (Ex_{in}) is the total incoming exergy fluctuation (J/yr), can be defined based on the energy budget of the country under investigation. Based on Sciubba (2011), the extended exergy accounting method determines the exergy corresponding to Labour, Money, and Ecological remediation (Eqs. 6.24 and 6.25) in goods or services by elements of "α" and "β" and some financial factors like GDP. These aspects are highly inspired by population, labor statistics, regular and international income, and normal workload. The stated aspects and exergy counterparts were examined and figured out by Sciubba (2011) for some developed and developing countries. For example, if setup cost ($K = €30$) and we consider the percentages of money, labor, and ecological remediation denote the order cost, e.g., 60%, 30%, and 10%, therefore, $K_{Cap} = 0.6 \times 30 = €18$, $K_L = 0.3 \times 30 = €9$ and $K_{Env} = 0.1 \times 30 = €3$. Considering Eqs. (6.21)-(6.25), one can calculate the three exergetic values of capital, labor, and environment $\left(ee_{Cap,K} + ee_{L,K} + ee_{Env,K}\right)$ related to setup/order cost to achieve exergy $K_{(x)}$.

6.4.2. Applying extended exergy accounting to fuzzy optimization of multi-buyer coal SC

Under the carbon trade policy, the exergy equivalent of the total cost is ($TC_{(x)} = Z_{(x)1} + Z_{(x)2} + Z_{(x)3} + Z_{(x)4}$), These equivalents can be done with the following formulas (Jawad et al. 2015)

$$K_{(x)i,s} = \left(ee_{Cap,K(i,s)} + ee_{L,K(i,s)} + ee_{Env,K(i,s)}\right) \tag{6.26}$$

$$K_{(x)ij,b} = \left(ee_{Cap,K(ij,b)} + ee_{L,K(ij,b)} + ee_{Env,K(ij,b)}\right) \tag{6.27}$$

$$h_{(x)ij} = \left(ee_{Cap,h(ij)} + ee_{L,h(ij)} + ee_{Env,h(ij)}\right) \tag{6.28}$$

$$s_{(x)1} = s_1 \times \left(ee_{Cap}\right) \tag{6.29}$$

$$s_{(x)2} = s_2 \times \left(ee_{Cap}\right) \tag{6.30}$$

$$t_{(x)f} = t_f \times \left(ee_{Cap}\right) \tag{6.31}$$

$$t_{(x)v} = t_v \times \left(ee_{Cap}\right) \tag{6.32}$$

$$t_{(x)L} = t_L \times \left(ee_{Cap}\right) \tag{6.33}$$

$$t_{(x)M} = t_M \times \left(ee_{Cap}\right) \tag{6.34}$$

$$\widetilde{C_{(x)\iota}} = \left(ee_{Cap,\widetilde{C(\iota)}} + ee_{L,\widetilde{C(\iota)}} + ee_{Env,\widetilde{C(\iota)}}\right) \tag{6.35}$$

$$C_{\widetilde{(x)trade}} = \widetilde{C_{trade}} \times \left(ee_{Cap}\right) \tag{6.36}$$

$$X_{(x)j} = X_j \times \left(ee_{Cap}\right) \tag{6.37}$$

Therefore, by using the above formulas to the objective functions and limitations of the model in Eq. (6.17), it is converted to a fuzzy exergy model as follows:

6.4.3. A fuzzy exergy modeling of coal SC with carbon trade policy

$$TC_{(x)trade} = \sum_{i}^{n}\sum_{j}^{m}\left[\frac{\widetilde{D_{ij}}}{Q_{ij}}\left(K_{(x)i,s}+K_{(x)ij,b}\right)+\frac{h_{(x)ij}}{2Q_{ij}\left(1-\frac{\widetilde{D_{ij}}}{P_i}\right)}\left(Q_{ij}(1-\delta_m)\left(1-\frac{\widetilde{D_{ij}}}{P_i}\right)-b_{ij}\right)^2 + \left(\frac{s_{(x)1}.\,b_{ij}^2}{2Q_{ij}\left(1-\frac{\widetilde{D_{ij}}}{P_i}\right)}+\frac{s_{(x)2}.\,b_{ij}.\,\widetilde{D_{ij}}}{Q_{ij}\left(1-\frac{\widetilde{D_{ij}}}{P_i}\right)}\right)\right]+\sum_{j}^{m}\widetilde{C_{(x)trade}}\times\left(e_j^+-e_j^-\right)$$
$$+\sum_{j}^{m}\left[x_{(x)j}^- + \left(int^-\times x_{(x)j}^-\right)-\left(int^+\times x_{(x)j}^+\right)\right]$$
$$+\sum_{i}^{n}\sum_{j}^{m}\left[\left(\frac{\widetilde{D_{ij}}}{Q_{ij}}.\,t_{(x)f}\right)+\left(Q_{ij}.\,t_{(x)v}\right)+\left(\frac{\widetilde{D_{ij}}}{Q_{ij}}.\,(Lo+Un).\left(t_{(x)L}+t_{(x)M}\right)\right)\right]$$

$s.t.$

$$\frac{\sum_i^n\sum_j^m C_{(x)0}\,.\,\widetilde{D_{ij}}}{\sum_i^n\sum_j^m \frac{C_{(x)0}.\left(Q_{ij}(1-\delta_m)\left(1-\frac{\widetilde{D_{ij}}}{P_i}\right)-b_{ij}\right)^2}{2Q_{ij}\left(1-\frac{\widetilde{D_{ij}}}{P_i}\right)}} \geq ITR_j$$

$$\sum_{i}^{n}\left[\left(Q_{ij}.\,\theta_m\right)+\left(\frac{\widetilde{D_{ij}}}{Q_{ij}}.\,L_j.\,\theta_t\right)+\left(Q_{ij}.\,\widetilde{D_{ij}}.\,\theta_k\right)\right]+\left(e_j^- - e_j^+\right)=E_j$$

$$\sum_{i}^{n}\sum_{j}^{m}\left[\left(Q_{ij}.\,\delta_m\right)+\left(Q_{ij}.\,(1-\delta_m).\,\delta_t\right)+\left(Q_{ij}(1-\delta_m).\,(1-\delta_t).\,\delta_k\right)\right]\leq F$$

$$\sum_{i}^{n}\left(Q_{ij}(1-\delta_m)\left(1-\frac{\widetilde{D_{ij}}}{P_i}\right)-b_{ij}\right)\leq W_j$$

$$\sum_{i}^{n}\left(\widetilde{C_{(x)i}}.\,Q_{ij}(1-\delta_m)\right)+\left(x_{(x)j}^+ - x_{(x)j}^-\right)=X_{(x)j}$$

$$\sum_{i}^{n}\sum_{j}^{m}\frac{\widetilde{D_{ij}}}{Q_{ij}}\leq N_{Max}$$

$$Q_{ij}\leq Q_{Max}$$

$$b_{ij}\leq Q_{ij}$$

$Q_{ij} > 0, integer, i = 1,2, \dots, n$

$b_{ij} \geq 0, integer, j = 1,2, \dots, m$

$$x^{+}_{(x)j}, x^{-}_{(x)j}, e^{+}_{j}, e^{-}_{j} \geq 0, \tag{6.38}$$

Under the extended exergy accounting technique, the following section suggests three recent metaheuristic algorithms to solve the fuzzy exergy model in Eq. (6.38).

6.5. A solution algorithm

In general, for solving optimization models like Eq. (6.38), there are three solution search methods such as exact (complete), heuristic, and metaheuristic (Shokouhifar and Jalali, 2017). The weakness of "Exact" approaches, for instance, LINGO, CPLEX, and GAMS are primarily on demanded CPU running time, particularly in real-size problems (Diabat 2014; Zahedi et al., 2016), while "heuristics" approaches do not explore the search space effectively (Naderi et al., 2021b). In contrast, "metaheuristics" algorithms have enhanced the global search implementation slightly (Yan et al., 2021; Guo et al., 2020) and have the most precision results with a reasonable CPU running time (Stojanovic et al., 2017). Since the model in Eq. (6.38) is "nonlinear integer-programming (NIP)" and "NP-complete," finding an "analytical solution" (if any) is demanding (Diabat, 2014; Gen and Cheng, 1997; Peng et al., 1998). The fact is that the objective function has a non-derivative arrangement, and the decision variables are integers (Roozbeh Nia et al., 2014). Optimization with metaheuristic algorithms is an influential and well-known method utilized in several engineering and real-world problems (Islam et al., 2021; Maier et al., 2019). These algorithms focus on improved reliability, enhanced system performance, efficient resources, superior system response, profit intensification, error, and cost reduction. (Maier et al., 2019).

Metaheuristic algorithms employ a stochastic manner for the optimization process created on random operators (Islam et al., 2021). Moreover, natural or biological phenomena have stimulated metaheuristic algorithms based on swarm intelligence and evolution (Abdullah and Ahmed, 2020; Islam and Ahmed, 2020) and applied them to various models (Wang et al., 2020a). Many researchers have successfully employed traditional swarm intelligence and evolutionary algorithms, for instance, ant colony optimization (ACO), particle swarm optimization (PSO), and genetic algorithm (GA) (Roozbeh Nia et al., 2017a, 2017b). Despite these algorithms, there are some modern and attractive examples involving the Horse herd Optimization Algorithm (HOA) (MiarNaeimi et al., 2021; Moldovan, 2020), Whale Optimization Algorithm (WOA) (Mirjalili and Lewis, 2016; Islam et al., 2021; Yan et al., 2021; Zhang and Wen, 2021; Wang et al., 2021b), Lion Optimization Algorithm (LOA) (Yazdani and Jolai, 2016; Varshney et al., 2021; Selvi and Ramakrishnan, 2020; Wang et al., 2020b; Gope et al., 2019), Ant Lion Optimizer (ALO) (Mirjalili, 2015; Wang et al., 2020a; Bekakra et al., 2021; Singh et al., 2021; Chen et al., 2020a; Pradhan et al., 2020), and Grey wolf optimizer (GWO) (Mirjalili et al., 2014; Padhy and Panda, 2021; Bekakra et al., 2021; Wang et al., 2021a; Liu et al., 2021; Tütüncü et al., 2021).

The GA and ACO presents a high risk of falling into local optimal, accordingly might lead to an inconsistent result thus needed more iteration to find the optimal solutions (Varshney et al., 2021). Moreover, GA, ACO and PSO have many factors, and it is complicated to decide on correct parameters (Shinoda and Miyata, 2019). In this study we consider three recent metaheuristic algorithms: ALO, LOA, and WOA, to solve the “exergy fuzzy NIP (EFNIP) problem” modeled in Eq. (38). The reasons for selecting these three modern algorithms are as follows:

- ALO has been demonstrated as an efficient optimization algorithm in many areas (Mirjalili, 2015; Dubey et al., 2016; Ali et al., 2017; Wang et al., 2020a) and has a good performance in deciding global optimum (Pradhan et al., 2020; Mirjalili, 2015). The crucial aspect of selecting ALO is by reason of its efficient search space employing random walk and choice of search agents by chance. (Pradhan et al., 2020). ALO has drawn extensive interest because of its relatively adequate efficiency, flexibility, and simplicity (Wang et al., 2020a).
- In most circumstances, the outcomes achieved by LOA deliver outstanding solutions in fast convergence and global optima accomplishment (Yazdani and Jolai, 2016). This approach uses the local as well as global optima and thus gives the optimal solution with minimum cost (fitness function) and takes less iteration (Varshney et al., 2021).
- WOA demands no added modification parameters to come to an outstanding balance between its exploration and exploitation (Aala Kalananda and Komanapalli, 2021). Study findings present that WOA is outstanding to other optimization methods, for instance, PSO, ACO, GA, differential evolution (DE), and gravitational search for solution precision and convergence speed (Chen et al., 2020c; Kaur and Arora, 2018; Mohammed et al., 2019, Jahromi et al., 2018). Since the benefits of effortless assumption, simple operation, straightforward application, few modification parameters, and strong robustness, the WOA algorithm has received widespread interest and has achieved many significant research outcomes (Du et al., 2021; Zhang et al., 2021; Long et al., 2020).

Based on the literature, metaheuristic algorithms' parameters substantially impact outcome quality and running time (Yang et al., 2009; Kao and Zahara, 2008). Consequently, the algorithm’s parameters employed are based on a pilot study, and the algorithm’s results will be validated with GAMS output in small-size problems. In the following subsections, short explanations primarily supported three metaheuristic algorithms. Interested readers are encouraged to see referred studies about these algorithms in detail. Afterward, the phases concerned in the proposed solutions are described.

6.5.1. The Ant Lion Optimization algorithm (ALO)

The Ant Lion Optimization algorithm, which Mirjalili (2015) proposed, is one of the nature-stimulated optimization procedures for solving one-dimensional and multidimensional optimization models (Pradhan et al., 2020). The algorithm is stimulated by the hunting behavior of antlions that catch their prey, ants, by digging a pit in the sand (Singh et al., 2021; Mirjalili, 2015). A larva of an ant lion builds a conical-formed hole by going along a spherical route in the sand and putting the sand with its enormous jaw. After excavating the hole, larvae conceal at the bottom, stopping for ants to be stuck in the hole. When an ant has been stuck in the hole, the ant lion drops sand towards the outside, so it falls its target into the hole. Once an ant is stuck into the jaw, the ant lion draws the prey toward itself and eats (Mirjalili, 2015; Chen et al., 2020a). Six main processes were planned in ALO to replicate communication between the ant and the ant lion in the hole, comprising of random walk of ants, getting caught in the ant lion’s trap, the construction of a hole, descending ants towards the ant lion, sticking prey, re-construction of the hole, and elitism, respectively (Mirjalili 2015; Wang et al., 2020a). An analysis of all prior studies on ALO is newly offered by (Heidari et al., 2020; Abualigah et al., 2020; Abderazek et al., 2020). Moreover, Appendix Fig. 6.A.1. presents pseudo-code of the ALO algorithm.

6.5.2. The lion optimization algorithm (LOA)

Yazdani and Jolai (2016) suggested Lion Optimization Algorithm (LOA) as a population-based metaheuristic approach. It is an optimization naturally motivated by the attributes of lions. It replicates lions' social and hunting performance, for instance, prey capturing, roaming, mating, and defence (Selvi and Ramakrishnan, 2020). The lion has specific social behavior; hence it is the most powerful mammal globally. Lions have two forms of social behavior: inhabitants and travelers, and lions can switch over them. Inhabitants live in parties known as pride, in which resident females and males appear to give birth. The second structural behavior is so-called travelers, who occasionally move about in pairs or singularly. A detailed explanation of all LOA steps is presented in Yazdani and Jolai (2016). Moreover, Appendix Fig. 6.A.2. presents pseudo-code of the LOA algorithm.

6.5.3. The whale optimization algorithm (WOA)

The whale optimization algorithm (WOA) is a recent swarm intelligence optimization method suggested by Mirjalili and Lewis (2016). The WOA algorithm is motivated by the hunting method of humpback whales. Their predation process is called the bubble-net attacking method, and it has been seen that it is done by producing unique bubbles along a circle (Goldbogen et al., 2013). The hunting behavior primarily includes three stages: search for prey, diminishing encircling, and spiral revising location (Mirjalili and Lewis, 2016; Wang et al., 2021b; Chen et al., 2020b, 2020c; Lee and Lu, 2020). The WOA uses three operators that simulate these phases. Among them, the operator replicating the bubble-net hunting behavior of humpback whales is an essential process in WOA (Li et al., 2021). In WOA, the location of each humpback whale stands for a search agent. During the search process, the whales progressively acquire the proper location of the prey by encircling, twisting, and capturing it at the end (Zhang et al., 2021). The WOA obtains the best solution to the global optimization problem by continuously revising the search agent (Yan et al., 2021). Moreover, WOA depends on a linearly declining vector whose value reduces from 2 to 0 as the repetitions develop (Aala Kalananda and Komanapalli, 2021). Appendix Fig. 6.A.3. presents pseudo-code of the WOA algorithm.

At the end of this section, the main steps in the recommended solution process of Eq. (38) under carbon trade emission policy and uncertain environment are presented in Fig. 6.1. Moreover, an illustration of the chromosomes related to the order quantity (Q) and backorder amount (b) of a numerical example with one supplier and ten buyers who have four products are presented in Fig. 6.2, correspondingly.

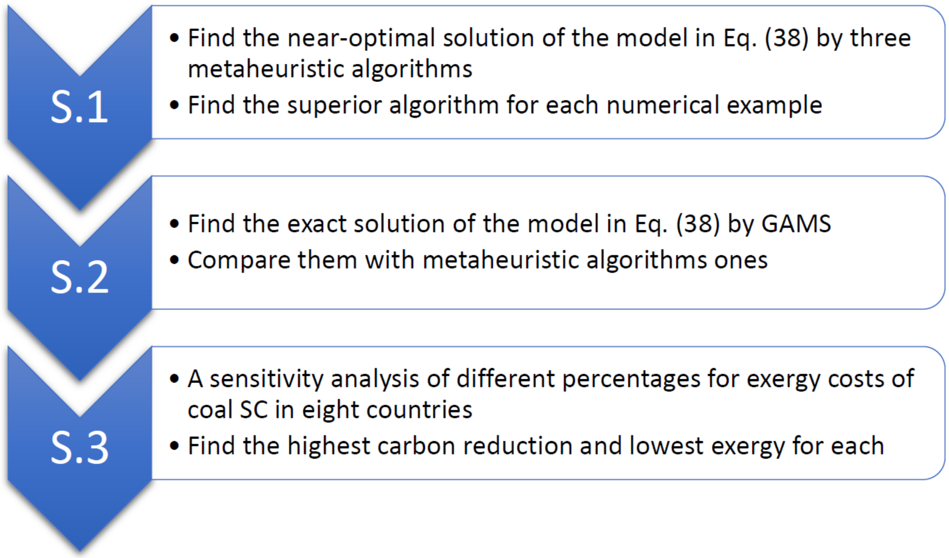


Fig.6.1. Flow chart of the proposed solving procedure

Q_{i1}:	1590	1343	1162	2001	Q_{i2}:	1135	1619	1167	1341
Q_{i3}:	1187	1838	1192	1673	Q_{i4}:	1183	1055	1857	2101
Q_{i5}:	1320	2216	1310	1076	Q_{i6}	1470	1486	1877	558
Q_{i7}:	1013	1023	1151	689	Q_{i8}:	1935	2104	1566	805
Q_{i9}:	1461	1099	1797	1404	Q_{i10}	1216	1427	2074	606

b_{i1}:	36	1	40	32	b_{i2}:	16	48	13	17
b_{i3}:	70	56	35	15	b_{i4}:	0	11	3	94
b_{i5}:	18	27	12	17	b_{i6}	74	64	15	21
b_{i7}:	23	10	15	68	b_{i8}:	35	21	66	0
b_{i9}:	61	0	67	14	b_{i10}	16	14	20	60

Fig.6.2. An example of the chromosomes for the numerical example with four products and ten buyers

6.6. Numerical examples

This section gives numerical test problems, including one real-world coal SC case study in Iran and nine arbitrary cases related to it. We are looking to optimize sustainability in a coal SC by considering the indirect (hidden) costs in Joules and including all three factors simultaneously (using the extended exergy accounting method) under a carbon trade policy in an uncertain environment. Based on the recommended solution steps in Fig. 6.1, we are examining to get the optimum value of six decision variables, such as the amount of required loan/investment for each buyer (x_j^-, x_j^+), the required carbon credits for each buyer (e_j^+, e_j^-), order quantity of each product for each buyer (Q_{ij}), and amount of backorder of each product for each buyer (b_{ij}). Moreover, a sensitivity analysis considers different percentages for exergy costs in coal SC of eight countries: Iran, India, China, Australia, Japan, Poland, the USA, and Zimbabwe to find the best exergy values that great the highest sustainability in each country. These countries are ranked in the top 20 countries with the most coal consumption globally (Statista, 2020).

6.6.1 Case study in Iran

The real-world case study includes one supplier and ten buyers of coal products in an SC in Iran. Tabas Parvadeh Coal Company (TPCCO), located in Tabas city, is the biggest coal producer in Iran. Consistent with the statistics printed by the Iranian Mines and Mining Industries Development and Renovation Organization (IMIDRO), TPCCO extracted 1.232 million tons of coal from March 21, 2019, to January 20, 2020. With about 1.15 billion tons of reserves, Iranian coal mines can deliver up to three million tons of coal concentrate yearly (IEA, clean coal center 2020). From another point of view, the production of steel in Iran is highly dependent on coal since metallurgical coal, or coking coal, is an essential part of steel-making operations. TPCCO produces four diverse types (grades) of coal, and this company has ten key customers (steel producers) in different cities in Iran. TPCCO and all buyers use the public rail transport system to transport coal orders. Since demand of each steel producer (buyer) for each type of coal, coal purchasing price, and carbon emission price is not stated precisely, we consider them trapezoidal fuzzy numbers (see Appendix Tables 6.A.1 & 6.A.2). Moreover, the initial data of the test problems (parameters and resource values) and their equivalent exergy parameters are presented in Appendix Tables 6.A.3-6.A.10, respectively. Moreover, all inventory costs and their equivalent exergy cost related to real case study in Iran are presented in Table 6.4. Consistent with the informed values in Sciubba (2011) as the only reference study for the extended exergy accounting method in the literature, we take equivalent exergy parameters of Egypt due to the resemblances between Iran and Egypt regarding economic development, population, religion, and culture. Therefore, exergy parameters of Iran and selected countries are presented in Table 6.5.

After consulting with SC managers of TPCCO, it was estimated that each cost of $K_{i,S}, K_{ij,b}, h_{ij}$ and C_i can be divided to *Cap*=30% for capital, *L*=60% for labor, and *Env*=10% for ecological remediation. In Subsection 4.1, we described the method of extended exergy accounting and related formulas that we applied to our model. For example, in Table 6.4, the cost of $K_{i,S}$ is assumed €20 for the first product which includes €6 (20 × 0.30), €12 (20 × 0.60) and €2 (20 × 0.10) (monetary values) for capital (*Cap*=30%), labor (*L*=60%) and environmental (*Env*=10%) remediation, respectively. Moreover, these three numbers are converted to the exergy values of 34.08, 3.56, and 11.36 *MJ*, respectively (in total $K_{(x)i,S}$ =49 *MJ*). To show better the performance of our suggested modern metaheuristic algorithms in solving big-size test problems, besides the actual case study, we considered nine arbitrary numerical examples related to it with 10, 20, 40, 80, 160, 320, 640, 1280, and 2560 products in a sustainable coal SC in Iran with one supplier and 15 buyers. The initial data of all numerical examples are shown in Appendix Tables (6.A.1)-(6.A.10), respectively. As noted previously, a pilot study is used for the parameter tuning of all suggested metaheuristic algorithms, and the test problems are solved on a PC with an Intel Core i7-7500U CPU with 2.70GHz and 8.00 GB RAM in Windows 10. The "MATLAB" 2017a software is also employed for coding all the algorithms.

Table 6.4: Inventory costs and their equivalent exergy based on capital (30%), labor (60%), and environment (10%) values (Test with four products)

	Prod.	value	Unit	Monetary values			Exergy values (MJ)			Total exergy	
				Cap.	L.	Env.	$ee_{Cap,i}$	$ee_{L,i}$	$ee_{Env,i}$		
$K_{i,S}$	i	20	Euro/order	6	12	2	34.08	3.56	11.36	49	$K_{(x)i,S}$
$K_{ij,b}$	i	15	Euro/order	4.5	9	1.5	25.56	2.67	8.52	36.75	$K_{(x)ij,b}$
C_i	1	200	Euro/unit	60	120	20	340.8	35.6	113.6	490	$C_{(x)i}$
	2	170		51	102	17	289.68	30.26	96.56	416.50	
	3	140		42	84	14	238.56	24.92	79.52	343.00	
	4	100		30	60	10	170.40	17.80	56.80	245.00	
h_{ij}	1	5	Euro/unit/year	1.5	3	0.5	8.52	0.89	2.84	12.25	$h_{(x)ij}$
	2	4		1.2	2.4	0.4	6.82	0.71	2.27	9.80	
	3	3		0.9	1.8	0.3	5.11	0.53	1.70	7.35	
	4	3		0.9	1.8	0.3	5.11	0.53	1.70	7.35	

Table 6.5: The exergy parameters of selected countries (sensitivity analysis) (Sciubba, 2011)

	Unit	Iran	Australia	China	India	Japan	Poland	USA	Zimbabwe
$\boldsymbol{\alpha_x}$	-	0.0121	0.018	0.0015	0.0419	0.773	0.55	0.145	0.0026
$\boldsymbol{\beta_x}$	-	2.94	1.69	0.477	1.32	1.9	0.57	1.43	3.9
$\boldsymbol{ee_{Cap}}$	MJ/Euro	5.68	3.56	14.01	4.34	3.35	14.02	2.85	3.35
$\boldsymbol{ee_L}$	MJ/WH	3.56	71.21	48.66	1.64	70.18	76.55	72.82	70.18

6.6.2 Solving phases and related results

6.6.2.1 Step one - Metaheuristic algorithms

Based on solving procedure (Fig. 6.1), at the first step, all suggested metaheuristic algorithms are executed 15 times for the fuzzy exergy model with carbon trade policy (Eq. 6.38). The outputs of algorithms include the lowest fuzzy total exergy (*MJ*), and the CPU times (*seconds*) are presented in Tables 6.6 and 6.7, respectively. Based on the results, the superior metaheuristic algorithm for the smallest fuzzy total exergy (*MJ*) and running times (*seconds*) could be found for the model (Eq. 6.38).

Concerning the fuzzy total exergy and in line with the fallouts shown in Table 6.6, ALO is the best algorithm (with 32,753,094.69 and 122,319,654.35 MJ) in the actual case study in Iran with four products as well as the numerical test with ten products, while for test problems from 20 to 2560 products, WOA is the best. For our large size test problems (640, 1280 & 2560 products), WOA gets the lowest fuzzy total exergy cost (3,964,974,414.68; 8,490,424,760.63 &

20,715,326,512.04 MJ) followed by LOA, and ALO, respectively (see Fig. 6.3). Regarding Appendix Fig. 6.A.4, performance improvement between top two algorithms from 20p to 80p test problems, are less since the results of them are very close together. But in large-size test problems the average performance enhancement between the results of WOA and LOA is about 90%, which means the results of WOA are outstanding. In opposition, ALO has the highest fuzzy total exergy (MJ) results in our medium and large-size test problems.

Considering the CPU time (Sec.), WOA is absolutely the best algorithm with the lowest running time in all test problems (see Fig. 6.4). For example, in our large-size test problems (640, 1280 & 2560 products), the WOA CPU times were 49.23, 78.89, and 154.47 (Sec.), respectively (see Table 6.7). Moreover, in large-size test problems, the average of WOA's performance improvement (%) with the second-best algorithm is about 700% which means WOA solves the models fast (see Appendix Fig. 6.A.5). Conversely, ALO has the highest CPU time among other algorithms in all test problems except for 1285 products, where LOA (with 829.7169 Sec.) is the worse algorithm (see Table 6.7). In Fig. 6.5, we presented some convergence diagrams of the smallest fuzzy total exergy by the proposed algorithms.

Table 6.6: The fuzzy total exergy (MJ) observed by the algorithms under carbon trade policy in Iran (Eq. 6.38)

Test	ALO	LOA	WOA	Min. (MJ)	The bests	Performance improvement (%)
4p	32,753,094.69	56,130,526.91	48,504,010.50	32,753,094.69	ALO-WOA-LOA	48.09
10p	122,319,654.35	291,716,085.98	265,533,078.08	122,319,654.35	ALO-WOA-LOA	117.08
20p	620,356,160.82	464,274,771.96	444,387,816.87	444,387,816.87	WOA-LOA-ALO	4.48
40p	1,229,059,326.54	606,789,259.79	556,126,023.95	556,126,023.95	WOA-LOA-ALO	9.11
80p	2,772,002,306.09	950,139,646.13	887,480,983.66	887,480,983.66	WOA-LOA-ALO	7.06
160p	6,468,347,547.44	2,366,142,295.46	1,010,480,171.31	1,010,480,171.31	WOA-LOA-ALO	134.16
320p	12,809,569,710.57	5,295,722,151.09	2,409,465,266.86	2,409,465,266.86	WOA-LOA-ALO	119.79
640p	28,098,451,686.15	7,622,351,301.01	3,964,974,414.68	3,964,974,414.68	WOA-LOA-ALO	92.24
1280p	57,806,847,743.44	18,118,616,031.71	8,490,424,760.63	8,490,424,760.63	WOA-LOA-ALO	113.40
2560p	112,083,644,493.09	37,319,812,944.67	20,715,326,512.04	20,715,326,512.04	WOA-LOA-ALO	80.16

Table 6.7: The CPU times (Sec.) of solving numerical examples by the algorithms under carbon trade policy in Iran (Eq. 6.38)

Test	ALO	LOA	WOA	Min. (Sec.)	The bests	Performance improvement (%)
4p	3.07	3.23	0.97	0.97	WOA-ALO-LOA	214.90
10p	8.29	7.53	1.52	1.52	WOA-LOA-ALO	395.23
20p	14.71	12.62	2.60	2.60	WOA-LOA-ALO	384.68
40p	27.78	26.81	4.03	4.03	WOA-LOA-ALO	565.62
80p	53.99	51.63	5.57	5.57	WOA-LOA-ALO	826.17
160p	104.94	98.24	8.72	8.72	WOA-LOA-ALO	1026.17
320p	207.59	190.57	18.37	18.37	WOA-LOA-ALO	937.27
640p	406.38	339.40	49.23	49.23	WOA-LOA-ALO	589.36
1280p	801.43	829.72	78.89	78.89	WOA-ALO-LOA	915.85
2560p	1,606.61	1,442.98	154.47	154.47	WOA-LOA-ALO	834.17

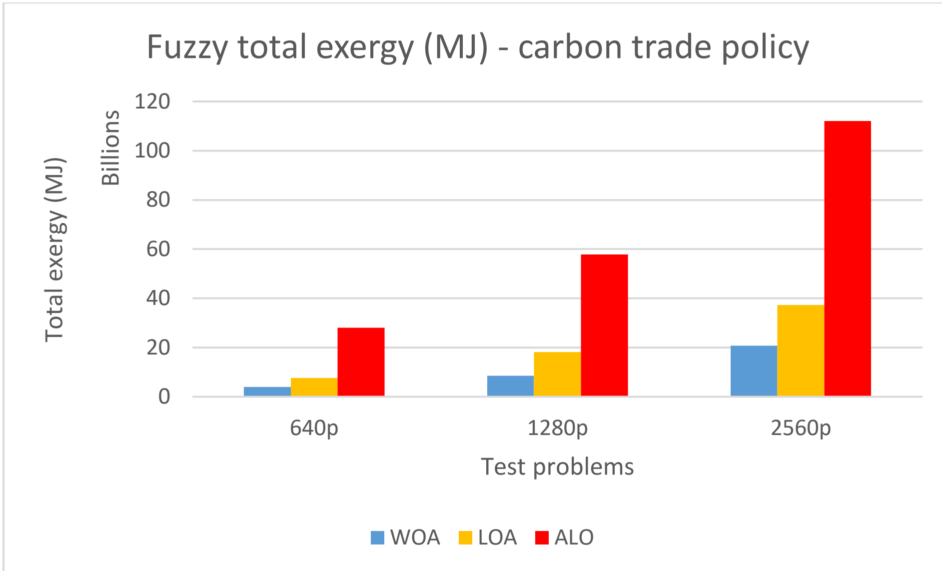


Fig.6.3. The total fuzzy exergy comparisons of algorithms in large size test problems (step 1)

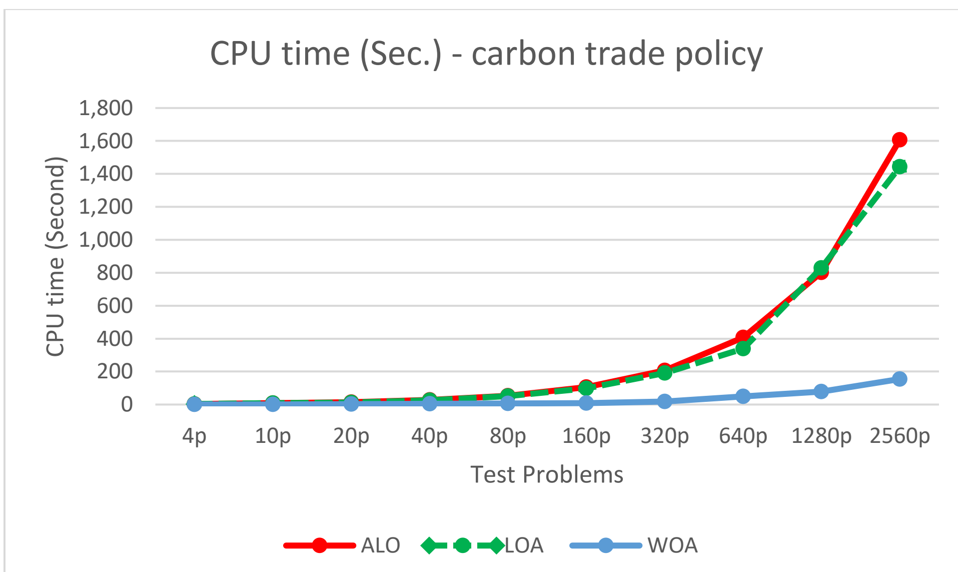
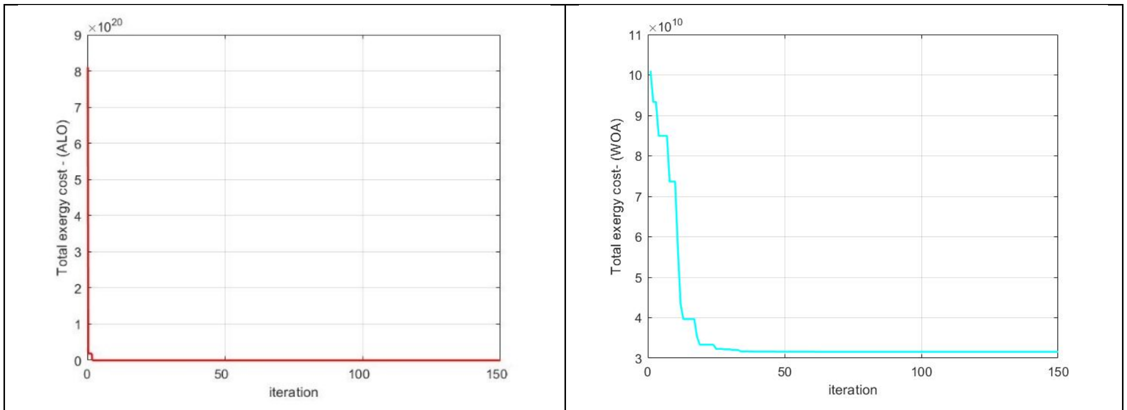


Fig.6.4. The CPU time comparisons of all algorithms (step 1)



ALO 4-product | WOA 2560-product

Fig.6.5. The convergence diagram of the total fuzzy exergy by the proposed algorithms (step 1)

6.6.2.2 Step two - Exact method

A solution may be compared with an "exact method" to validate the results by suggested algorithms. Exact optimizer software, for example, "GAMS" or an optimization library in "Python," can find the "exact result." In this research, the proposed mathematical model (Eq. 6.38) under carbon trade strategy is solved in small size (test with four products) by GAMS. A contrast with the best metaheuristic algorithm is made in Table 6.8. Taking into account Eq. (38) for the 4-product test problem, the exact result for the fuzzy total exergy is 31,537,292.44 (MJ), while the outcome of the best metaheuristic algorithm (ALO) for this test is 32,753,094.69 (MJ). Therefore, the percentage penalty between the exact method and ALO is 3.86% (see Table 6.8). Because the percentage penalty is minor, suggesting the excellent dominance of the solutions got by the best-suggested algorithm (Cárdenas-Barrón et al., 2012) since it is remarkably close to the exact method (see Fig. 6.6). Concerning CPU running time and Table 6.8, the distinction between exact method and ALO is 1.21 (Sec.), but the percentage penalty is 39.48%. It shows that the metaheuristic algorithm (ALO) solved the carbon trade model more rapidly (see Appendix Fig. 6.A.6).

Table 6.8: Comparing the results of the exact method (GAMS) with the best algorithm (ALO)

	ALO	Exact	Difference	Penalty (%)
Fuzzy total exergy:	32,753,094.69	31,537,292.44	1,215,802.25	3.86
CPU time:	3.07	4.28	1.21	39.48

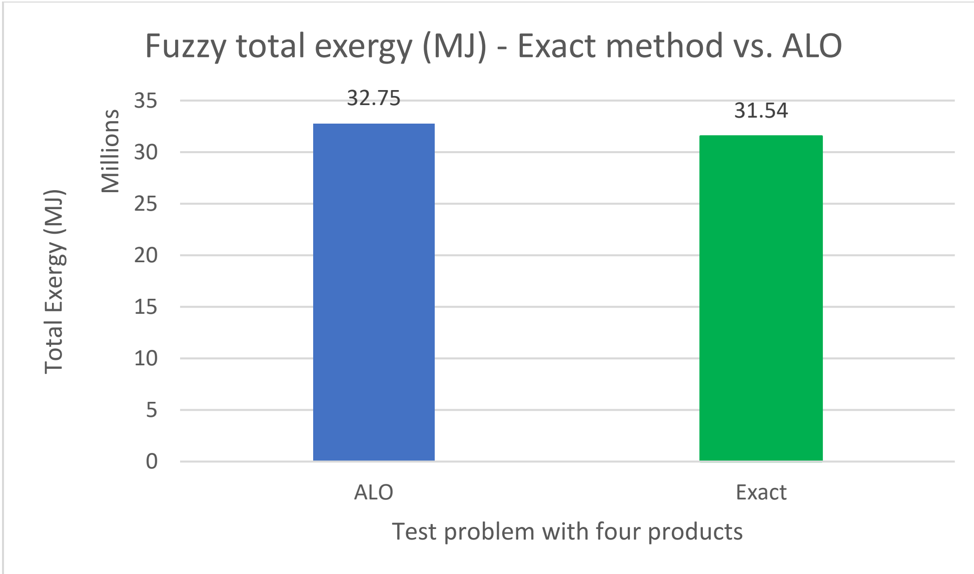


Fig.6.6. Comparison of the total fuzzy exergy between exact method and the best metaheuristic algorithm for test problem with four products (step 2)

6.6.2.3 Step three- Sensitivity analysis

In the earlier subsections, we studied the optimization of a sustainable fuzzy EPQ model of coal SC in Iran by taking into account different objectives simultaneously: the costs of the inventory system, an additional required budget of each buyer, coal transportation cost among SC members, and carbon emission cost. All goals in the models and related limitations under the emission trade strategy are in *MJ* in place of monetary values. This step tries to balance economic and sustainable advantages for coal SC companies. Considering that our proposed model is sustainable, we modify the exergy percentage for capital, labor, and environmental remediation by a sensitivity analysis to find the best values of exergy components that improve the sustainability of coal SC more than before. Additionally, to gain further insight into this adjustment, we evaluate sustainable coal SC in Iran as well as seven selected developing and developed countries with the world's most significant coal consumption. They are India, China, Australia, Japan, Poland, the USA, and Zimbabwe (Statista, 2020). We assumed the same coal SC and products for all these countries to make a comparative analysis. In the previous section, we mentioned that in our numerical examples, it was assumed that each cost of $K_{i,S}, K_{ij,b}, h_{ij}$ *and* C_i can be allocated to *Cap*=30% for capital, *L*=60% for labor, and *Env*=10% for ecological remediation (consider it as exergy Set A). In this section, to get more insight, we have changed these percentages to make seven different exergy sets (see Appendix Fig. 6.A.7), including A (30-60-10), B (60-20-20), C (20-50-30), D (20-40-40), E (20-30-50), F (30-10-60) and G (33-33-33). Considering each exergy set, we computed the fuzzy total exergy for a 4-item test problem under carbon trade policy for all countries by GAMS (see Table 6.9). For example, we consider coal SC in the USA and exergy Set C (*Cap*=20%, *L*=50%, and *Env*=30%), then employing extended exergy accounting method to convert all monetary costs of $K_{i,S}, K_{ij,b}, h_{ij}$ *and* C_i to equivalent (MJ). After that, we run model Eq. (38) with four product test problems using the Exact method (GAMS). Likewise, the same process was done for other exergy Sets (A-G) and considering other countries' coal SC. Finally, all results are presented in Table 6.9. In the following we explain the results in detail.

Table 6.9: Sensitivity analysis of different percentages for exergy elements (example with four products)

Sets (%) *	Fuzzy total exergy (Emission trade) MJ								Min. (MJ)	Country min.	Max. (MJ)	Country max.
	AU**	CH	IN	IR	JA	PO	US	ZI				
A (30-60-10)	37,386,644.58	121,884,457.74	32,520,676.90	31,537,292.44	38,038,472.22	106,551,302.66	31,673,757.27	31,803,458.12	31,537,292.44	Iran	121,884,457.74	China
B (60-20-20)	27,362,603.27	109,229,963.03	56,664,303.08	50,042,180.33	40,279,208.50	110,155,055.08	22,604,564.59	23,779,747.58	22,604,564.59	USA	110,155,055.08	Poland
C (20-50-30)	36,172,081.05	83,731,242.82	24,826,136.13	35,822,252.13	30,489,673.91	86,131,627.76	29,064,237.19	26,772,135.64	24,826,136.13	India	86,131,627.76	Poland
D (20-40-40)	30,457,341.89	94,201,685.52	32,528,308.04	43,914,327.75	36,862,147.59	92,933,114.17	31,090,827.64	25,762,854.83	25,762,854.83	Zimbabwe	94,201,685.52	China
E (20-30-50)	35,641,776.33	111,411,481.62	43,026,717.09	43,802,295.45	36,228,006.97	109,302,825.19	25,320,951.45	28,886,560.45	25,320,951.45	USA	111,411,481.62	China
F (30-10-60)	24,251,604.43	128,734,240.79	29,354,458.87	49,114,885.31	22,873,547.02	123,315,602.00	19,675,609.14	22,873,547.02	19,675,609.14	USA	128,734,240.79	China
G (33-33-33)	33,163,723.31	121,351,102.11	31,623,790.11	44,552,827.66	32,432,070.96	118,125,544.27	29,934,368.36	24,146,338.65	24,146,338.65	Zimbabwe	121,351,102.11	China
Min.	24,251,604.43	83,731,242.82	24,826,136.13	31,537,292.44	22,873,547.02	86,131,627.76	19,675,609.14	22,873,547.02	**Min. Min. (MJ)**		**Max. Max. (MJ)**	
Set Min.	F	C	C	A	F	C	F	F	19,675,609.14	USA	128,734,240.79	China
Max.	37,386,644.58	128,734,240.79	56,664,303.08	50,042,180.33	40,279,208.50	123,315,602.00	31,673,757.27	31,803,458.12				
Set Max.	A	F	B	B	B	F	A	A				

*Set (Cap%-L%-Environment%); **AU: Australia, CH: China, IN: India, IR: Iran, JA: Japan, PO: Poland, US: the USA, ZI: Zimbabwe

6.6.2.3.1 Analysis of each country

Considering Table 6.9 and Fig. 6.7, for coal SC in each country, we have:

- **Australia:** For coal SC under the carbon trade policy in this country, the top exergy components are Set F (30-10-60) since more exergy percentage is assumed for Environment (60%) and less for Labor (10%). It created the minimum fuzzy total exergy of 24,251,604.43 (MJ) for coal SC. Besides, the worst exergy components are Set A (30-60-10) since Labor has 60% while Environment has only 10%, which created the highest fuzzy total exergy with 37,386,644.58 (MJ).
- **China:** The best exergy components are Set C (20-50-30) when Labor has 50% weight, followed by Environment (30%) and Capital (20%), respectively. It created the minimum fuzzy total exergy of 83,731,242.82 (MJ) for coal SC. Likewise, the weakest exergy components are Set F (30-10-60) when more exergy percentage is assumed for Environment (60%) and only 10% for Labor, which generated the greatest fuzzy total exergy of 128,734,240.79 (MJ).
- **India:** Like China, the finest exergy components in India are Set C (20-50-30), when Labor has 50% weight, while Environment and Capital are 30% and 20%, respectively. It produced the minimum fuzzy total exergy of 24,826,136.13 (MJ) for coal SC. Moreover, the unpleasant exergy components are Set B (60-20-20) when more weight is expected for Capital (60%) and the same weights (20%) for Labor and Environment, which formed the maximum fuzzy total exergy of 56,664,303.08 (MJ).
- **Iran:** For coal SC in this country, the top exergy components are Set A (30-60-10) as Labor has 60% while Environment has only 10%. It made the minimum fuzzy total exergy of 31,537,292.44 (MJ). Like India, the unhealthiest exergy components in Iran are Set B (60-20-20) when more weight is assigned to Capital (60%) and the same weights for Labor and Environment (20%), which generated the maximum fuzzy total exergy of 50,042,180.33 (MJ).
- **Japan:** Like Australia, the best exergy components in Japan are Set F (30-10-60), while more exergy percentage is given to Environment (60%) and less to Labor (10%). It established the least amount of fuzzy total exergy with 22,873,547.02 (MJ) for coal SC. Furthermore, the unhealthiest exergy components are Set B (60-20-20) when more weight is provided to Capital (60%) and the same weights for Labor and Environment (20%), which generated the highest fuzzy total exergy of 40,279,208.50 (MJ).
- **Poland:** Like India and China, the excellent exergy components in Poland are Set C (20-50-30), when Labor has 50% weight, followed by Environment (30%) and Capital (20%), respectively. It created the least possible fuzzy total exergy of 86,131,627.76 (MJ) for coal SC. Besides, the worst exergy components are Set F (30-10-60), when more exergy percentage is offered to Environment (60%) and less on Labor (10%), which created the maximum fuzzy total exergy of 123,315,602.00 (MJ).
- **The USA:** Like Australia and Japan, the superior exergy components in the USA are Set F (30-10-60) as more exergy percentage is assumed to Environment (60%) and less on Labor (10%). It generated the minimum fuzzy total exergy of 19,675,609.14 (MJ) for coal SC. Additionally, the harmful exergy components are Set A (30-60-10) since Labor has 60% while Environment has only 10%, which established the highest fuzzy total exergy of 31,673,757.27 (MJ).
- **Zimbabwe:** Like Australia, Japan and the USA, the first-rate exergy components in Zimbabwe are Set F (30-10-60) because more exergy percentage is assumed to

Environment (60%) and less on Labor (10%). It crafted the minimum fuzzy total exergy of 22,873,547.02 (MJ) for coal SC. Additionally, the weakest exergy components are Set A (30-60-10) since Labor has 60% while Environment has only 10%, which generated the greatest fuzzy total exergy of 31,803,458.12 (MJ).

- Considering Table 6.9, the best total exergy (MJ) in each country is as follow: Australia (24,251,604.43), China (83,731,242.82), India (24,826,136.13), Iran (31,537,292.44), Japan (22,873,547.02), Poland (86,131,627.76), the USA (19,675,609.14) and Zimbabwe (22,873,547.02).
- Among all presented countries, the coal SC in the USA has the smallest total exergy (19,675,609.14 MJ), followed by Japan, Zimbabwe, Australia, India, Iran, China, and Poland, respectively (see Fig. 6.7).
- Moreover, coal SC in China creates the highest total exergy for all exergy sets except for Set B (60-20-20) and Set C (20-50-30) related to Poland (see Fig. 6.8).

6.6.2.3.2 Analysis of each exergy set

Considering Table 6.9, Fig. 6.8, and Appendix Fig. 6.A.7, for each exergy set, we have:

- **Exergy Set A (30%-60%-10%):** This exergy set has 60% for Labor, while for Environment, it is only 10%. Although this set works well for coal SC in Iran, with the minimum total exergy of 31,537,292.44 (MJ), in China, it is 121,884,457.74 (MJ).
- **Exergy Set B (60%-20%-20%):** In this set, more weight is assumed for Capital (60%) and the same for Labor and Environment (20%). Despite coal SC in Poland (110,155,055.08 MJ), exergy set B operates well in the USA with 22,604,564.59 (MJ).
- **Exergy Set C (20%-50%-30%):** In this set, Labor has 50% weight, followed by Environment (30%) and Capital (20%), respectively. Exergy set C performs well in coal SC in India (24,826,136.13 MJ), even though in Poland, the total exergy is 86,131,627.76 (MJ).
- **Exergy Set D (20%-40%-40%):** In this set, Capital has only 20% while 40% is for both Labor and Environment. In spite of the high result in China with 94,201,685.52 (MJ), exergy set D runs well in Zimbabwe with 25,762,854.83 (MJ).
- **Exergy Set E (20%-30%-50%):** In this set, 50% is assigned to Environment and 20% and 30% to Capital and Labor, respectively. Exergy set E operates well in the USA with 25,320,951.45 (MJ), although the result is high in China (111,411,481.62 MJ).
- **Exergy Set F (30%-10%-60%):** In this set, 60% is allocated to Environment and only 10% Labor. Exergy set F performs well in the USA (19,675,609.14 MJ), despite the fact that the result is not healthy in China (128,734,240.79 MJ).
- **Exergy Set G (33%-33%-33%):** In this set, all three exergy components have equal 33% weight. Even though exergy set G does not perform well in China with 121,351,102.11 (MJ), it runs well in Zimbabwe with 24,146,338.65 (MJ).
- Moreover, exergy Sets B (30-60-10), E (20-30-50) and F (30-10-60) created the minimum total exergy for coal SC in the USA, while all exergy sets except Set B (30-60-10) and Set C (20-50-30) created the highest total exergy in China (see Fig. 6.8).

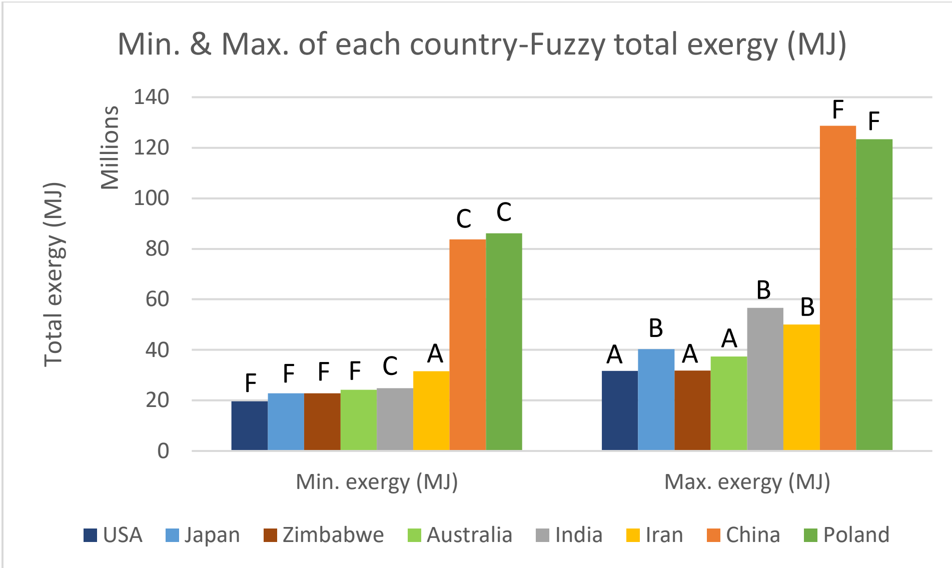


Fig.6.7. Sensitivity analysis for each country – Min. & Max. of the total fuzzy exergy (step 3)

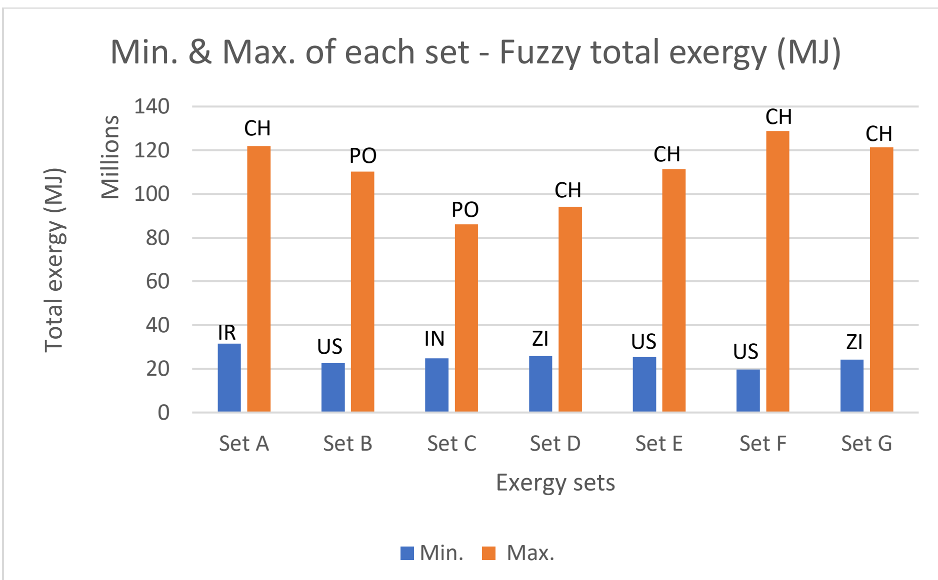


Fig.6.8. Sensitivity analysis for each set - Min. & Max. of the total fuzzy exergy (step 3)

6.7. Conclusions and future work

According to the literature review, there is a lack of studies that assess a coal SC under a carbon trade policy with ambiguous parameters such as carbon price and customer demand. Likewise, it is scarce to obtain research that assesses a SC in terms of Joules (in place of traditional monetary measures of performance) and simultaneously evaluates all sustainability characteristics, such as economic, labour, and environmental. Similarly, to the best of the authors' knowledge, no exergy analysis method like the extended exergy accounting in the literature considers carbon policy in SC. Therefore, this study develops the work in the papers by Jawad et al. (2016) and Naderi et al. (2021a) to a multi-product multi-limitation inventory (EPQ) model with backorder for a coal SC in Iran under an uncertain environment. By applying the extended exergy accounting technique and Mega-Joules (*MJ*) as a universal unit of measure, the total exergy of the coal SC can be calculated. Moreover, a well-known carbon reduction strategy (carbon trade) is employed to evaluate the sustainability performance of the model. In this study, we presented four research questions (in Section 6.3) and attempted to answer them.

Q1. Is it possible to assess the sustainability of coal SC under a carbon reduction policy in terms of Joules rather than money, to benefit both the economy and the environment?

In subsection 6.3.4, we developed a non-exergy mathematical model of the coal SC for carbon trade policy. Then the model has converted to a fuzzy model in subsection 6.3.5, and finally, a new SC assessment method called the extended exergy accounting (in terms of Joules) was employed in section 6.4. This method contains energy and material's main aggregate exergy subject and costs corresponding to economic externality (labor and capital) and ecological externality (environmental remediation). Therefore, employing this method could benefit both the economy and the environment. After that, three recent metaheuristic algorithms (ALO, LOA, and WOA) are utilized. When contrasting the best algorithm outcomes in small-size test problems (four products) with the exact method (GAMS), there is a small percentage error (3.86%) under the carbon trade policy between them. Therefore, it could validate the results of metaheuristic algorithms in this study.

Q2. Generally speaking, coal SC in developing countries, or even China, has the lowest overall cost; however, considering sustainability aspects (social, economic, and environmental characteristics) in terms of Joules, does this assumption still hold true?

Regarding the sensitivity analysis in subsection 6.6.2.3, we compared the sustainability of coal SC in eight developed and developing countries, such as Iran, India, China, Australia, Japan, Poland, the USA, and Zimbabwe (see Table 6.9). They are the world's most significant coal-consuming countries (Statista, 2020). It was observed that, Poland and China have the highest fuzzy total exergy of a sustainable coal SC (86,131,627.76 and 83,731,242.82 MJ, respectively) among eight selected countries. The reason behind this issue is that traditional assessment methods consider economic measures. In contrast, the method of extended exergy accounting (as mentioned in Section 6.4) considers all three aspects of sustainability (Labour, Money, and Ecological remediation) in goods or services. It determines the exergy corresponding to them (in terms of Joules) by some elements significantly affected by population, normal workload, labor statistics, and local and international wages in each country. Therefore, the extended exergy accounting results show the total number of Joules that coal SC utilized in Labour, Money, and Ecological aspects.

Q3. Which country has the most sustainable coal SC in terms of Joules?

Based on Table 6.9, the lowest total exergy of a sustainable coal SC among all eight countries belongs to the USA (19,675,609.14 MJ) under the carbon trade policy. It means sustainable coal mining and related processes in the USA have economic and environmental advantages compared to China or developing countries such as Iran and Zimbabwe. Moreover, Japan, Zimbabwe, Australia, India, Iran, China, and Poland followed the USA (see Fig. 6.7).

Q4. What is the best percentage of exergy components (social, economic, environmental characteristics) to achieve the greatest saving wherever coal SCs are working?

Considering subsection 6.2.3 and Table 6.9, it is observed that under carbon trade policy, exergy Set F (30-10-60) percentages created the minimum fuzzy total exergy (highest carbon and exergy reduction) in coal SC of the countries such as Australia, Japan, the USA, and Zimbabwe. Set F (30-10-60) is given more weight (60%) to Environment, 30% to Capital and only 10% to Labor. Likewise, for coal SC in China, India, and Poland, exergy Set C (20-50-30) generated the least amount of fuzzy total exergy (83,731,242.82; 24,826,136.13 & 86,131,627.76 MJ respectively). In Set C (20-50-30), the emphasis is on Labor with 50% weight, while Capital and Environment have 20% and 30%, respectively. Finally, for coal SC in Iran, Set A (30-60-10) has the best exergy component with the minimum fuzzy total exergy of (31,537,292.44 MJ). Labor with 60% is the first weight in Set A (30-60-10), while only 10% was assigned to Environment and 30% to Capital.

Moreover, the theoretical and managerial implications of this work are presented as follows:

It is important to note that the EEA method has the advantage of enabling meaningful comparisons between coal SCs in different countries that produce the same coal type. By comparing the amount of exergy consumed in the coal production process and related SC processes, it becomes easier to determine where a coal SC business should be located. Due to this, selecting a product from a country with low wages, such as China or India, may not always be beneficial as more exergy is required for its production. Using the EEA method provides an indication of the sustainability impact of coal SCs in an era when climate change concerns are increasing prevalent.

The exergy equations in Section 6.4 (for instance, Eqs. 6.26-6.37) show that all exergy parameters in Table 6.5 are directly related to the cost elements of inventory models (such as setup, purchasing, and holding), and affect the exergy functioning of the coal SC in a significant way. It is therefore critical to decrease the cost elements of a coal SC's inventory model to improve sustainability. The managers could use stock classification and shorter order cycles, reducing the lead time of suppliers, eliminating obsolete inventory, implementing a Just-in-Time inventory system, and monitoring key performance indicators.

Unlike conventional financial and commercial models, the results of our study found that despite assumptions that inventory parameters in coal SC are unchanged for all eight countries, more savings could be achieved through the tuning of exergy's inflows and outflows in each country. It means that no fixed amount of exergy components (Capital, Labor and Environment) can deliver the highest sustainability in all countries. According to our results in Table 6.9, set F (30-10-60) with 60% weight allocated to the environment and only 10% to labor generates the greatest sustainability for the USA (19,675,609.14 MJ) as well as the most unpleasant sustainability for China (128,734,240.79 MJ). Hence, finding the most appropriate values of the exergy components of the SC would be another task for decision makers.

Another point is that, considering Table 6.5, one can conclude that the exergy parameter of Capital ($ee_{Cap} = 2.85$ MJ/Euro) in the USA is less than the other countries. In contrast, China and Poland have the highest exergy parameter of Capital ($ee_{Cap} = 14.01$ & 14.02 MJ/Euro) among other countries. This would be one of the reasons why the USA has the most sustainable coal SC in terms of Joules whereas China and Poland are the least sustainable. Therefore, a way to increase sustainability in each country is to find ways to decrease exergy parameters. If we look at Eqs. (6.24) and (6.25), exergy parameters of (ee_{Cap}, ee_L) are dependent on two econometric coefficients (α_x, β_x) as well as (Ex_{in}). Subsection 6.4.1 explains that these are influenced by the type of societal organization, the historical period, the technological level, the pro-capital resource consumption, and the geographical location of the country (Sciubba, 2011). All shareholders, governments, individuals, societies, business organisations, scientists, etc., need to contribute significantly to adjusting parameters, if possible. An example is controlling the import and export of goods from and to the country, or extracting ores and minerals. Promoting locally made goods can be a way for individuals, societies, and business organizations to support this cause. As a result, there would be more jobs available in the country, and increasing the labor force rate (Jawad et al., 2018). Additionally, effective productivity growth (output per hour worked) can boost a country's income and GDP per capita. For more information, readers are encouraged to consult Sciubba (2011).

In addition, decision-makers should find ways to improve the sustainability of their coal SC by reducing waste, labor, material, and pollution, which will reduce the damaging effects of coal SC. When calculating energy costs, managers of SC would have more flexibility since they could use available resources rather than just capital to calculate the quantity. Furthermore, this research will also guide managers of international coal mining companies who wish to decide which country has more sustainable conditions for their business and investments. Furthermore, the EEA method in this study is subject to some limitations, including the following:

- When EEA is employed to a coal SC, the precision of the outcomes is dependent upon the assumptions made.
- It is possible that the EEA method in coal SCs may have limitations when more than one country is involved in the SC processes (international companies).
- Insufficient data regarding a country's total exergy input, the quantity of exergy represented in the workforce, the exergy of raw materials and energy consumed to supply a coal.

The following avenues for future research are suggested for consideration:

a) A coal production system.
b) An international coal SC model that works in more than one country at the same time.
c) Comparing a global coal SC with a national one.
d) A model with multi-objective (integrating inventory measures).
e) The strategy of increasing carbon price with increasing the amount of carbon (price dependent on amount) by each company.
f) The SC of coal power plants.
g) Quantity discounts in cost per unit of products can be allowed.
h) Multi-echelon SCs, for example, single-buyer multi-supplier and multi-buyer multi-supplier SCs, can be investigated.
i) Lead times can be included.

Postscripts:

This chapter considered carbon trade policy for coal SC to improve the sustainability of coal SC in both developed and developing countries by incorporating extended exergy accounting. In the next chapter, carbon cap policy will be applied to coal SC. Additionally, carbon offset policy will be presented in Chapter 8, as additional material.

Paper Appendix-Chapter 6

Table 6.A.1. Fuzzy demands of 15 buyers (*j*) and 10 products (*i*) (values: *1000)

j	i=1	i=2	i=3	i=4	i=5	i=6	i=7	i=8	i=9	i=10
1	(100, 110, 125,150)	(70, 80, 95, 120)	(65, 68, 72, 75)	(16, 18, 21, 26)	(115, 118, 122, 125)	(85, 88, 91, 97)	(66, 68, 71, 76)	(16, 18, 21, 26)	(112, 118, 121, 130)	(82, 88, 91, 100)
2	(100, 110, 125,150)	(60, 70, 85, 110)	(55, 58, 62, 65)	(16, 18, 21, 26)	(115, 118, 122, 125)	(75, 78, 81, 87)	(56, 58, 61, 66)	(16, 18, 21, 26)	(112, 118, 121, 130)	(72, 78, 81, 90)
3	(90, 100, 115, 140)	(60, 70, 85, 110)	(55, 58, 62, 65)	(11, 13, 16, 21)	(105, 108, 112, 115)	(75, 78, 81, 87)	(56, 58, 61, 66)	(11, 13, 16, 21)	(102, 108, 111, 120)	(72, 78, 81, 90)
4	(70, 80, 95, 120)	(40, 50, 65, 90)	(35, 38, 42, 45)	(6, 8, 11, 16)	(85, 88, 92, 95)	(55, 58, 61,67)	(36, 38, 41, 46)	(6, 8, 11, 16)	(82, 88, 91, 100)	(52, 58, 61, 70)
5	(60, 70, 85, 110)	(40, 50, 65, 90)	(25, 28, 32, 35)	(5, 7, 10, 15)	(75, 78, 82, 85)	(55, 58, 61,67)	(26, 28, 31, 36)	(5, 7, 10, 15)	(72, 78, 81, 90)	(52, 58, 61, 70)
6	(50, 60, 75, 100)	(30, 40, 55, 80)	(15, 18, 22, 25)	(4, 6, 9, 14)	(65, 68, 72, 75)	(45, 48, 51, 57)	(16, 18, 21, 26)	(4, 6, 9, 14)	(62, 68, 71, 80)	(42, 48, 51, 60)
7	(40, 50, 65, 90)	(20, 30, 45, 70)	(10, 13, 17, 20)	(3, 5, 8, 13)	(55, 58, 62, 65)	(35, 38, 41, 47)	(11, 13, 16, 21)	(3, 5, 8, 13)	(52, 58, 61, 70)	(32, 38, 41, 50)
8	(30, 40, 55, 80)	(10, 20, 35, 60)	(5, 8, 12, 15)	(2, 4, 7, 12)	(45, 48, 52, 55)	(25, 28, 31, 37)	(6, 8, 11, 16)	(2, 4, 7, 12)	(42, 48, 51, 60)	(22, 28, 31, 40)
9	(20, 30, 45, 70)	(10, 20, 35, 60)	(3, 6, 10, 13)	(1, 3, 6, 11)	(35, 38, 42, 45)	(25, 28, 31, 37)	(4, 6, 9, 14)	(1, 3, 6, 11)	(32, 38, 41, 50)	(22, 28, 31, 40)
10	(10, 20, 35, 60)	(0, 10, 25, 50)	(0, 3, 7, 10)	(0, 2, 5, 10)	(25, 28, 32, 35)	(15, 18, 21, 27)	(1, 3, 6, 11)	(0, 2, 5, 10)	(22, 28, 31, 40)	(12, 18, 21, 30)
11	(100, 110, 125,150)	(70, 80, 95, 120)	(65, 68, 72, 75)	(16, 18, 21, 26)	(115, 118, 122, 125)	(85, 88, 91, 97)	(66, 68, 71, 76)	(16, 18, 21, 26)	(112, 118, 121, 130)	(82, 88, 91, 100)
12	(100, 110, 125,150)	(60, 70, 85, 110)	(55, 58, 62, 65)	(16, 18, 21, 26)	(115, 118, 122, 125)	(75, 78, 81, 87)	(56, 58, 61, 66)	(16, 18, 21, 26)	(112, 118, 121, 130)	(72, 78, 81, 90)
13	(90, 100, 115, 140)	(60, 70, 85, 110)	(55, 58, 62, 65)	(11, 13, 16, 21)	(105, 108, 112, 115)	(75, 78, 81, 87)	(56, 58, 61, 66)	(11, 13, 16, 21)	(102, 108, 111, 120)	(72, 78, 81, 90)
14	(70, 80, 95, 120)	(40, 50, 65, 90)	(35, 38, 42, 45)	(6, 8, 11, 16)	(85, 88, 92, 95)	(55, 58, 61,67)	(36, 38, 41, 46)	(6, 8, 11, 16)	(82, 88, 91, 100)	(52, 58, 61, 70)
15	(60, 70, 85, 110)	(40, 50, 65, 90)	(25, 28, 32, 35)	(5, 7, 10, 15)	(75, 78, 82, 85)	(55, 58, 61,67)	(26, 28, 31, 36)	(5, 7, 10, 15)	(72, 78, 81, 90)	(52, 58, 61, 70)

* Demand values are repeated for test problems with greater than ten products

Table 6.A.2. Fuzzy parameters for 15 buyers (*j*) and 10 products (*i*) (values: *10)

	i=1	i=2	i=3	i=4	i=5	i=6	i=7	i=8	i=9	i=10
$\widetilde{C_i}$:	(5, 8, 12, 15)	(9, 12, 16, 19)	(12, 15, 19, 22)	(15, 18, 22, 25)	(5, 8, 12, 15)	(9, 12, 16, 19)	(12, 15, 19, 22)	(15, 18, 22, 25)	(5, 8, 12, 15)	(9, 12, 16, 19)
$\widetilde{C_{trade}}$ =(33.6, 36.6, 40.6, 43.6)		$\widetilde{C_0}$ =(5, 8, 12, 15)								

* Parameter values are repeated for test problems with greater than ten products

Table 6.A.3. Initial data (monetary value) of test problem with ten products and their equivalent of exergy values (MJ)

Prod.	Cost values				Exergy equivalent			
(i)	$K_{i,S}$	$K_{ij,b}$	h_{ij}	C_i	$K_{(x)i,S}$	$K_{(x)ij,b}$	$h_{(x)ij}$	$C_{(x)i}$
1	20	15	5	200	49	36.75	14.94	597.67
2	20	15	4	170	49	36.75	11.95	508.02
3	20	15	3	140	49	36.75	8.97	418.37
4	20	15	3	100	49	36.75	8.97	298.83
5	20	15	5	200	49	36.75	14.94	597.67
6	20	15	4	170	49	36.75	11.95	508.02
7	20	15	3	140	49	36.75	8.97	418.37
8	20	15	3	100	49	36.75	8.97	298.83
9	20	15	5	200	49	36.75	14.94	597.67
10	20	15	4	170	49	36.75	11.95	508.02

* These values are repeated for test problems with greater than 10 products

Table 6.A.4. Initial data of the actual case study in Iran with four products (without exergy)

$P_i = (780000, 550000, 320000, 110000)$	s_1=3, s_2=0
$L_j = (635, 586, 1084, 1028, 763, 1102, 382, 688, 603, 877)$	int^{-}=0.04, int^{+}=0.02
$E_j = (18000, 16800, 15800, 12000, 10700, 8900, 7400, 5500, 5000, 3700)$	$\theta_m = 3.18 \times 10^{-3}$
$X_j = (290000, 290000, 300000, 290000, 300000, 280000, 280000, 280000, 280000, 280000)$	$\theta_t = 1.4 \times 10^{-5}$
$W_j = (6400, 6500, 6600, 6900, 7000, 7100, 7200, 7300, 7400, 7500)$	$\theta_k = 5 \times 10^{-5}$
$t_f = 10;\ t_v = 15;\ t_l = 12;\ t_m = 8$;	$\delta_m = 0.10;\ \delta_t = 0.08;\ \delta_k = 0.12$
$N_{max} = 1300$; $F = 22000$; $ITR = 17$; $Q_{max} = 2500$	$L_O = 1;\ U_n = 2.5$

Table 6.A.5. Equivalent exergy parameters of the actual case study in Iran with four products

$t_{(x)f} = 56.80;\ t_{(x)v} = 85.20;\ t_{(x)l} = 68.16;\ t_{(x)m} = 45.44$

$Labor\ cost = 12;\ C_{(x)trade} = 2192;$

$s_{(x)1} = 17.04;\ s_{(x)2} = 0$

$X_{(x)j} = (1647200, 1647200, 1704000, 1647200, 1704000, 1590400, 1590400, 1590400, 1590400, 1590400)$

Table 6.A.6. Warehouse space (W_j) of each buyer in all examples (10-2560 products)

	10p	20p	40p	80p	160p	320p	640p	1280p	2560p
Buyer 1	16,500	33,000	66,000	132,000	264,000	528,000	1,056,000	2,112,000	4,224,000
Buyer 2	16,600	33,200	66,400	132,800	265,600	531,200	1,062,400	2,124,800	4,249,600
Buyer 3	16,700	33,400	66,800	133,600	267,200	534,400	1,068,800	2,137,600	4,275,200
Buyer 4	17,200	34,400	68,800	137,600	275,200	550,400	1,100,800	2,201,600	4,403,200
Buyer 5	17,300	34,600	69,200	138,400	276,800	553,600	1,107,200	2,214,400	4,428,800
Buyer 6	17,500	35,000	70,000	140,000	280,000	560,000	1,120,000	2,240,000	4,480,000
Buyer 7	17,600	35,200	70,400	140,800	281,600	563,200	1,126,400	2,252,800	4,505,600
Buyer 8	17,800	35,600	71,200	142,400	284,800	569,600	1,139,200	2,278,400	4,556,800
Buyer 9	17,900	35,800	71,600	143,200	286,400	572,800	1,145,600	2,291,200	4,582,400
Buyer 10	18,000	36,000	72,000	144,000	288,000	576,000	1,152,000	2,304,000	4,608,000
Buyer 11	16,500	33,000	66,000	132,000	264,000	528,000	1,056,000	2,112,000	4,224,000
Buyer 12	16,600	33,200	66,400	132,800	265,600	531,200	1,062,400	2,124,800	4,249,600
Buyer 13	16,700	33,400	66,800	133,600	267,200	534,400	1,068,800	2,137,600	4,275,200
Buyer 14	17,200	34,400	68,800	137,600	275,200	550,400	1,100,800	2,201,600	4,403,200
Buyer 15	17,300	34,600	69,200	138,400	276,800	553,600	1,107,200	2,214,400	4,428,800

Table 6.A.7. Available budget (X_j) of each buyer (exergy values) in all examples (10-2560 products)

	10p	20p	40p	80p	160p	320p	640p	1280p	2560p
Buyer 1	4,260,000	8,520,000	17,040,000	28,400,000	56,800,000	113,600,000	221,520,000	443,040,000	886,080,000
Buyer 2	4,260,000	8,520,000	17,040,000	32,376,000	64,752,000	129,504,000	227,200,000	454,400,000	908,800,000
Buyer 3	3,976,000	7,952,000	15,904,000	30,672,000	61,344,000	122,688,000	227,200,000	454,400,000	908,800,000

Buyer 4	3,976,000	7,952,000	15,904,000	30,672,000	61,344,000	122,688,000	227,200,000	454,400,000	908,800,000
Buyer 5	3,805,600	7,611,200	15,222,400	30,444,800	60,889,600	121,779,200	227,200,000	454,400,000	908,800,000
Buyer 6	3,805,600	7,611,200	15,222,400	30,444,800	60,889,600	121,779,200	232,880,000	465,760,000	931,520,000
Buyer 7	3,805,600	7,611,200	15,222,400	30,444,800	60,889,600	121,779,200	224,360,000	448,720,000	897,440,000
Buyer 8	3,748,800	7,497,600	14,995,200	29,990,400	59,980,800	119,961,600	224,360,000	448,720,000	897,440,000
Buyer 9	3,748,800	7,497,600	14,995,200	29,990,400	59,980,800	119,961,600	232,880,000	465,760,000	931,520,000
Buyer 10	3,578,400	7,156,800	14,313,600	28,627,200	57,254,400	114,508,800	223,792,000	447,584,000	895,168,000
Buyer 11	3,578,400	7,156,800	14,313,600	28,627,200	57,254,400	114,508,800	219,248,000	438,496,000	876,992,000
Buyer 12	3,578,400	7,156,800	14,313,600	28,627,200	57,254,400	114,508,800	226,064,000	452,128,000	904,256,000
Buyer 13	3,521,600	7,043,200	14,086,400	28,172,800	56,345,600	112,691,200	223,792,000	447,584,000	895,168,000
Buyer 14	3,521,600	7,043,200	14,086,400	28,172,800	56,345,600	112,691,200	223,792,000	447,584,000	895,168,000
Buyer 15	3,521,600	7,043,200	14,086,400	28,172,800	56,345,600	112,691,200	223,792,000	447,584,000	895,168,000

Table 6.A.8. Permitted carbon emission (E_j) of each buyer in all examples (10-2560 products)

	10p	**20p**	**40p**	**80p**	**160p**	**320p**	**640p**	**1280p**	**2560p**
Buyer 1	41,000	82,000	164,000	270,000	530,000	1,060,000	2,080,000	4,160,000	8,320,000
Buyer 2	38,000	76,000	152,000	285,000	560,000	1,120,000	2,000,000	4,000,000	8,000,000
Buyer 3	36,000	72,000	144,000	255,000	500,000	1,000,000	1,900,000	3,800,000	7,600,000
Buyer 4	26,000	52,000	104,000	190,000	370,000	740,000	1,420,000	2,840,000	5,680,000
Buyer 5	23,000	46,000	92,000	184,000	365,000	730,000	1,320,000	2,640,000	5,280,000
Buyer 6	18,000	36,000	72,000	144,000	285,000	570,000	1,110,000	2,220,000	4,440,000
Buyer 7	13,000	26,000	52,000	104,000	200,000	400,000	800,000	1,600,000	3,200,000
Buyer 8	9,000	18,000	36,000	72,000	140,000	280,000	560,000	1,120,000	2,240,000
Buyer 9	7,000	14,000	28,000	56,000	110,000	220,000	440,000	880,000	1,760,000
Buyer 10	3,000	6,000	12,000	24,000	45,000	90,000	180,000	360,000	720,000
Buyer 11	41,000	82,000	164,000	295,000	580,000	1,160,000	2,170,000	4,340,000	8,680,000
Buyer 12	38,000	76,000	152,000	270,000	530,000	1,060,000	2,000,000	4,000,000	8,000,000
Buyer 13	36,000	72,000	144,000	270,000	530,000	1,060,000	1,850,000	3,700,000	7,400,000
Buyer 14	26,000	52,000	104,000	200,000	400,000	800,000	1,520,000	3,040,000	6,080,000
Buyer 15	23,000	46,000	92,000	184,000	365,000	730,000	1,400,000	2,800,000	5,600,000

Table 6.A.9. Initial data of the resources of all examples (4-2560 products)

	4p	10p	20p	40p	80p	160p	320p	640p	1280p	2560p
Nmax	1300	8200	19000	43,000	96,000	192,000	405,000	840,000	1,680,000	3,500,000
ITR	17	17	20	20	20	20	20	20	20	20
F	22000	82000	164000	328,000	656,000	1,312,000	2,624,000	5,248,000	10,496,000	20,992,000

Table 6.A.10. The exergy values of inventory parameters (values in MJ) for 1^{st} product (i=1)

Country		$ee_{Cap(i,s)}$	$ee_{L(i,s)}$	$ee_{Env(i,s)}$	Total
Iran	$K_{(x)i,S}$	34.08	3.56	11.36	49
	$K_{(x)ij,b}$	25.56	2.67	8.52	36.75
	$h_{(x)ij}$	8.52	0.89	2.84	12.25
	$C_{(x)i}$	340.80	35.60	113.60	490
Australia	$K_{(x)i,S}$	21.36	71.21	7.12	99.69
	$K_{(x)ij,b}$	16.02	53.41	5.34	74.77
	$h_{(x)ij}$	5.34	17.80	1.78	24.92
	$C_{(x)i}$	213.60	712.10	71.20	996.90
China	$K_{(x)i,S}$	84.06	48.66	28.02	160.74
	$K_{(x)ij,b}$	63.04	36.49	21.01	120.56
	$h_{(x)ij}$	21.02	12.17	7.01	40.19
	$C_{(x)i}$	840.60	486.60	280.20	1607.40
India	$K_{(x)i,S}$	26.04	1.64	8.68	36.36
	$K_{(x)ij,b}$	19.53	1.23	6.51	27.27
	$h_{(x)ij}$	6.51	0.41	2.17	9.09
	$C_{(x)i}$	260.40	16.40	86.80	363.60
Japan	$K_{(x)i,S}$	20.10	70.18	6.70	96.98
	$K_{(x)ij,b}$	15.07	52.63	5.02	72.74
	$h_{(x)ij}$	5.03	17.55	1.68	24.25
	$C_{(x)i}$	201	701.80	67	969.80
Poland	$K_{(x)i,S}$	84.12	76.55	28.04	188.71
	$K_{(x)ij,b}$	63.09	57.4125	21.03	141.53

	$h_{(x)ij}$	21.03	19.14	7.01	47.18
	$C_{(x)i}$	841.20	765.50	280.40	1887.10
The USA	$K_{(x)i,S}$	17.1	72.82	5.7	95.62
	$K_{(x)ij,b}$	12.82	54.61	4.27	71.72
	$h_{(x)ij}$	4.28	18.21	1.43	23.91
	$C_{(x)i}$	171.00	728.20	57.00	956.20
Zimbabwe	$K_{(x)i,S}$	20.1	70.18	6.7	96.98
	$K_{(x)ij,b}$	15.07	52.63	5.02	72.74
	$h_{(x)ij}$	5.03	17.55	1.68	24.25
	$C_{(x)i}$	201.00	701.80	67.00	969.80

Initialize the first population of ants and antlions randomly
Calculate the fitness of ants and antlions
Find the best antlions and assume it as the elite (determined optimum)
while *the end criterion is not satisfied*
  for *every ant*
    Select an antlion using Roulette wheel
    Update c and d
    Create a random walk and normalize it
    Update the position of ant
  end for
  Calculate the fitness of all ants
  Replace an antlion with its corresponding ant it if becomes fitter
  Update elite if an antlion becomes fitter than the elite
end while
Return *elite*

Figure 6.A.1. Pseudo-code of the ALO algorithm (Mirjalili, 2015).

1. Generate random sample of Lions N_{pop}(N_{pop} is number of initial population).
2. Initiate prides and nomad lions
   i. Randomly select %N (Percent of lions that are nomad) of initial population as nomad lion. Partition remained lions into P (P is number of prides) prides randomly, and formed each pride's territory.
   ii. In each pride %S (Sex rate) of entire population are known as females and the rest as males. This rate in nomad lions is inversed.
3. For each pride do
   i. Some randomly selected female lion go hunting.
   ii. Each of remained female lion in pride go toward one of the best selected position from territory.
   iii. In pride, for each resident male; %R (Roaming percent) of territory randomly are selected and checked.
   %Ma (Mating probability) of females in pride mate with one or several resident male. → *New cubs become mature.*
   iv. Weakest male drive out from pride and become nomad.
4. For Nomad do
   i. Nomad lion (both male and female) moving randomly in search space.
   %Ma (Mating probability) of nomad Female mate with one of the best nomad male. → *New cubs become mature.*
   ii. Prides randomly attacked by nomad male.
5. For each pride do
   i. Some female with I rate ((Immigrate rate)) immigrate from pride and become nomad.
6. Do
   i. First, based on their fitness value each gender of the nomad lions are sorted. After that, the best females among them are selected and distributed to prides filling empty places of migrated females.
   ii. With respect to the maximum permitted number of each gender, nomad lions with the least fitness value will be removed.

If termination criterion is not satisfied, then go to step 3

Figure 6.A.2. Pseudo-code of the LOA algorithm (Yazdani and Jolai, 2016).

```
Initialize the whales population Xi (i = 1, 2, ..., n)
Calculate the fitness of each search agent
X*=the best search agent
while (t < maximum number of iterations)
    for each search agent
    Update a, A, C, l, and p
        if1 (p<0.5)
            if2 (|A| < 1)
                Update the position of the current search agent
            else if2 (|A| ≥ 1)
                Select a random search agent (X_rand)
                Update the position of the current search agent
            end if2
        else if1 (p≥0.5)
                Update the position of the current search
      end if1
    end for
    Check if any search agent goes beyond the search space and amend it
    Calculate the fitness of each search agent
    Update X* if there is a better solution
    t=t+1
end while
return X*
```

Figure 6.A.3. Pseudo-code of the WOA algorithm (Mirjalili and Lewis, 2016).

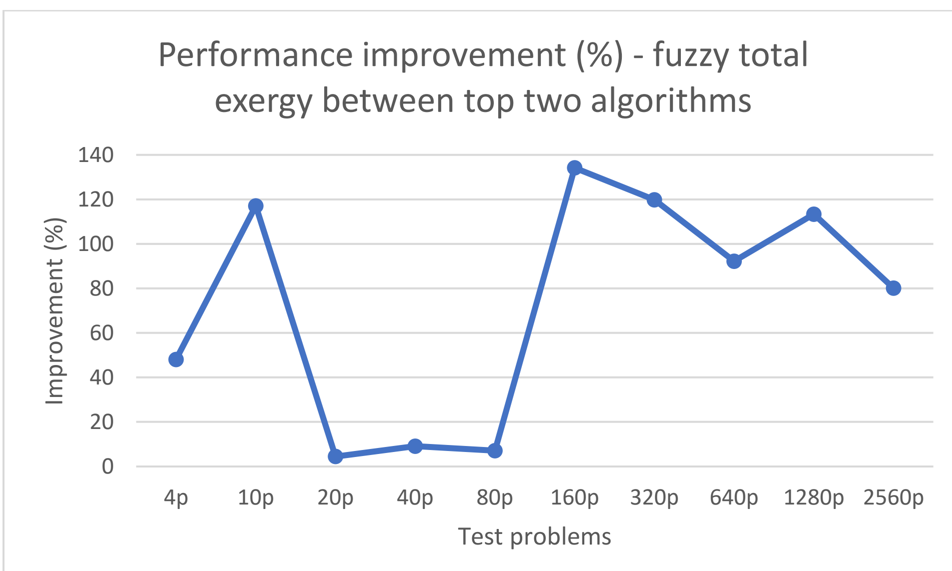


Figure 6.A.4. Performance improvement (%) between top two algorithms in the total fuzzy exergy (step 1)

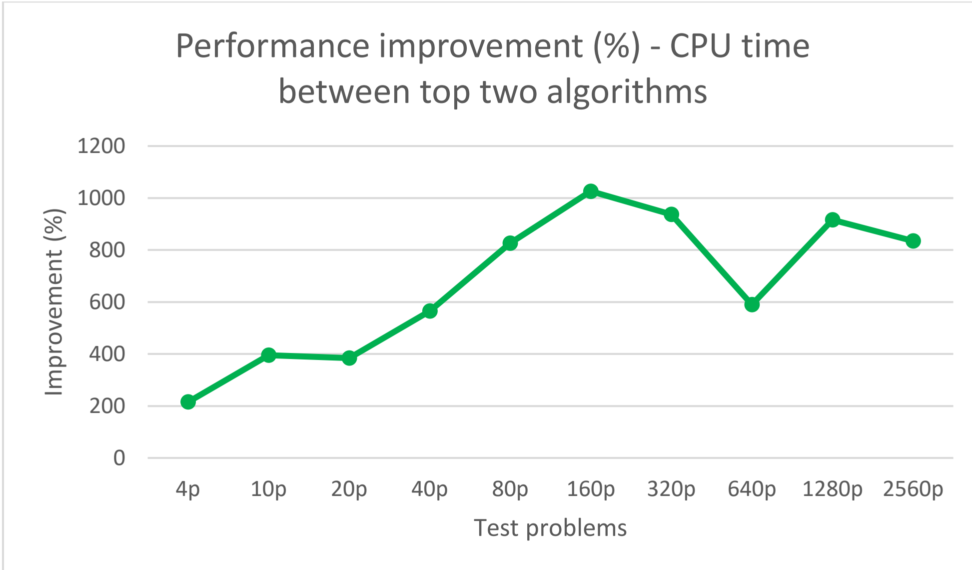


Figure 6.A.5. Performance improvement (%) of CPU time between top two algorithms (step 1)

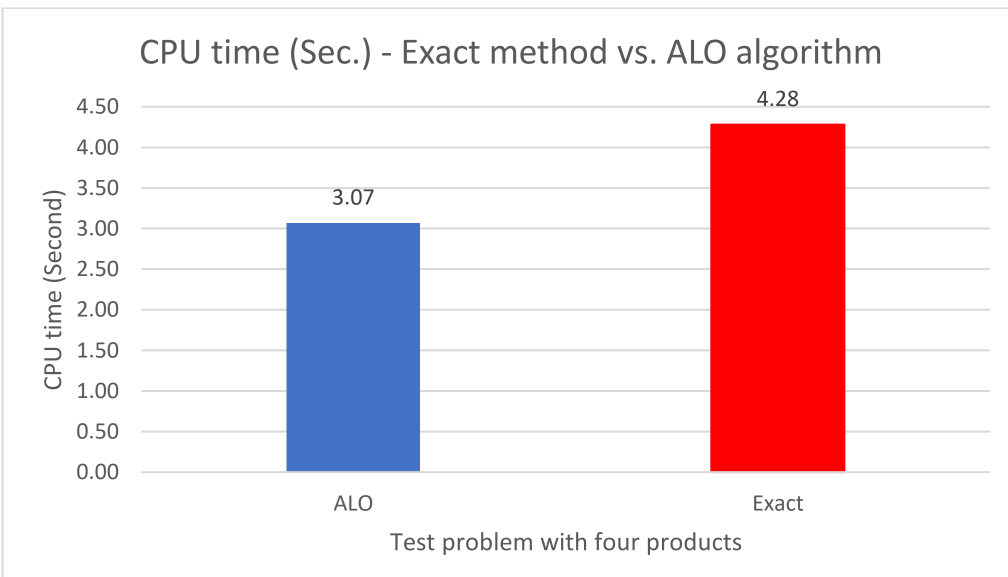


Figure 6.A.6. Comparison of CPU time between exact method and ALO algorithm for test problem with four products (step 2).

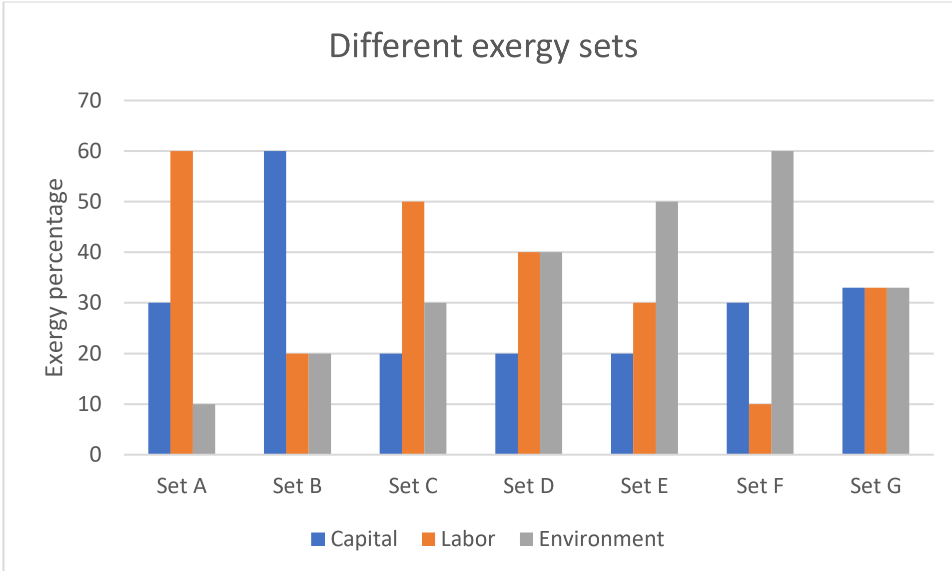


Figure 6.A.7. Seven exergy sets (capital, labor & environment) for coal SC.

CHAPTER 7. ADDITIONAL RESULTS FOR CHAPTER 5

Forewords

Previous chapters considered carbon tax and trade policies for coal SC. Now, this chapter follows Chapter 5 while considers carbon cap policy to improve the sustainability of coal SC in both developed and developing countries by extended exergy accounting. Moreover, carbon offset policy will be presented in Chapter 8, as additional material.

As mentioned in Chapter 1, the main carbon pricing policies are carbon tax, carbon cap, carbon offset, and carbon trade (Malladi and Sowlati, 2020), whereas each carbon policy has different costs and carbon reductions. The advantages of employing each carbon emission policy are not equal for companies involved in coal SC. While some carbon policies are more environmentally friendly, others are more economically beneficial. In Chapter 5, carbon tax policy was applied to a EOQ model of the coal SC and then the model converted to a sustainable coal SC (in terms of Joules) by using EEA method. Now, this chapter extends the EOQ model and results presented in Chapter 5 by applying the carbon cap policy. To make a comparison between the results of the model under carbon tax and cap policies, the same assumptions, and concepts (as Chapter 5) are used here.

The following subsections will develop a non-exergy EOQ model of the coal SC for carbon cap policy. Then the model is converted to an exergy fuzzy model in terms of Joules by applying the EEA method.

7.1. A non-exergy Modeling of coal SC with carbon cap policy

7.1.1. Objective function

In the model under carbon cap policy, three objectives are defined. First, the total inventory cost of coal SC (TC_1) include the ordering (TO_{ij}), holding (TH_{ij}), stockout (TS_{ij}), purchasing (TP_{ij}), and transportation (TT_{ij}) costs (Pasandideh et al. 2010, 2011; Razmi et al. 2010) as

$$TC_1 = TO_{ij} + TH_{ij} + TS_{ij} + TP_{ij} + TT_{ij} \tag{7.1}$$

Where,

$$TO_{ij} = \sum_{i}^{n} \sum_{j}^{m} \frac{D_{ij}}{Q_{ij}} \left(A_{i,s} + A_{ij,b}\right) \tag{7.2}$$

$$TH_{ij} = \sum_{i}^{n} \sum_{j}^{m} \frac{h_{ij}}{2Q_{ij}} \left(Q_{ij}(1-\alpha) - b_{ij}\right)^2 \tag{7.3}$$

$$TS_{ij} = \sum_{i}^{n} \sum_{j}^{m} \left(\frac{s_1 . b_{ij}^2}{2Q_{ij}} + \frac{s_2 . b_{ij} . D_{ij}}{Q_{ij}}\right) \tag{7.4}$$

$$TP_{ij} = \sum_{i}^{n}\sum_{j}^{m} C_i D_{ij} \tag{7.5}$$

$$TT_{ij} = \sum_{i}^{n}\sum_{j}^{m} \frac{D_{ij}}{Q_{ij}}(A_{ij,t}) \tag{7.6}$$

Where (D_{ij}, Q_{ij}, h_{ij}) are the demand rate of coal i for buyer j, order quantity of item i for buyer j and holding cost per unit of coal i for buyer j, respectively. Second, the total cost associated with the additional required budget of all buyers. In our model, the over-achievement budget (B_j^-) is considered as the cost. It means the buyer should get a loan (B_j^- as a decision variable) with an interest rate of (int^-). In this case, the buyer should pay this loan and the corresponding interest rate $(B_j^- + [int^- \times B_j^-])$ after the end of the year. Consequently, the whole cost related to the budget of all buyers (TC_2) is

$$TC_2 = \sum_{j}^{m}\left[B_j^- + \left(int^- \times B_j^-\right)\right] \tag{7.7}$$

Third, to make the model green, we consider that all coal SC processes produced some wastes (imperfect quality items such as coal refuse, coal waste, and coal tailings) which to be discarded to the environment. This waste has a penalty cost as

$$TC_3 = C_{waste} \times \sum_{i}^{n}\sum_{j}^{m}\left[\left(Q_{ij}.\alpha\right) + \left(Q_{ij}.(1-\alpha).\beta\right) + \left(Q_{ij}(1-\alpha).(1-\beta).\gamma\right)\right] \tag{7.8}$$

Where (α, β, γ) are the proportions of imperfect quality items in mining, transportation, and steel manufacturer processes, respectively. Moreover, C_{waste} is the unit cost of imperfect quality items produced by different supply chain processes. So, the combination of the above three objectives $(TC_{cap} = TC_1 + TC_2 + TC_3)$ makes the non-exergy total cost of coal SC under emission cap policy.

7.1.2. The limitations

The emission cap policies imply that each buyer inside the coal SC can merely manufacture within an assumed emission cap (Cap_j). If this quantity surpasses the emission cap, the related buyer will hinder manufacture until the carbon emissions comply with the cap (Yang et al., 2018). Consequently, a limitation on carbon emissions is included in the problem with the emission cap strategies.

$$\sum_{j}^{m}\sum_{i}^{n}\left[\left(Q_{ij}.f_m\right) + \left(\frac{D_{ij}}{Q_{ij}}.L_j.f_t\right) + \left(Q_{ij}.D_{ij}.f_k\right)\right] \le Cap_j \tag{7.9}$$

Where (f_m, f_t, f_k) are emissions factors in mining, transportation, and steel manufacturer processes, respectively. Moreover, L_j is the distance between the coal vendor and buyer j. This constraint is the summation of produced carbon in mining, transportation, and steelmaking processes, respectively. As revealed earlier, a real-world VMI prescribed contract includes the vendor and all the buyers in the coal SC. This type of VMI contract accepting a limitation for the available budget of each buyer (B_j) and taking into account related costs for this issue can be expressed as follows:

$$\sum_{j}^{m}\sum_{i}^{n} C_i . Q_{ij}(1-\alpha) \leq B_j + \left(B_j^{-}\right) \tag{7.10}$$

Where (C_i) is purchasing price per unit of item i. Eq. (7.10) demonstrates that if the total paid out money of a buyer is greater than the available budget ($\sum_i^n C_i . Q_{ij}(1-\alpha) > B_j$), then the buyer needs to get a loan with the amount of ($B_j^{-} > 0$). This amount (B_j^{-}) is not determined before since it is a decision variable in the model, and in Eq. (7.7), the total cost related to this constraint is formulated. Moreover, the storage capacity of each buyer (F_j) is constrained (Cárdenas-Barrón et al. 2012),

$$\sum_{j}^{m}\sum_{i}^{n}\left(Q_{ij}(1-\alpha) - b_{ij}\right) \leq F_j \tag{7.11}$$

Furthermore, the railway transportation system among a vendor and all buyers has some limitations for its capacity. So, the Min. (V_i) and Max. (W_i) of the transportation capacity for each order quantity (Q_{ij}) are

$$V_i \leq Q_{ij} \leq W_i \tag{7.12}$$

In addition, the vendor has a limitation for its total sales capacity (G), which is as follows:

$$\sum_{i}^{n}\sum_{j}^{m} Q_{ij} \leq G \tag{7.13}$$

Likewise, there is a constraint on the total number of orders (N) by all buyers:

$$\sum_{i}^{n}\sum_{j}^{m} \frac{D_{ij}}{Q_{ij}} \leq N \tag{7.14}$$

Lastly, the j^{th} buyer's highest amount of backorder of an item i in a cycle should be fewer than or equal to its lot size amount (Q_{ij}). Therefore

$$b_{ij} \leq Q_{ij} \tag{7.15}$$

It should be stated that for simplification of the mathematical model, we ignore the cost of purchasing (Eq. 7.5) in the model. With regards to Eqs. (7.1)-(7.15), the model of "multi-item" SVMB EOQ with the VMI strategy under carbon cap policy can be easily obtained as

$$TC_{cap} = \sum_{i}^{n}\sum_{j}^{m}\left[\frac{D_{ij}}{Q_{ij}}\left(A_{i,s} + A_{ij,b}\right) + \frac{h_{ij}}{2Q_{ij}}\left(Q_{ij}(1-\alpha) - b_{ij}\right)^2 + \left(\frac{s_1.b_{ij}^2}{2Q_{ij}} + \frac{s_2.b_{ij}.D_{ij}}{Q_{ij}}\right)\right.$$
$$\left.+\frac{D_{ij}}{Q_{ij}}\left(A_{ij,t}\right)\right] + \sum_{j}^{m}\left[B_j^- + \left(int^- \times B_j^-\right)\right]$$
$$+ C_{waste} \times \sum_{i}^{n}\sum_{j}^{m}\left[\left(Q_{ij}.\alpha\right) + \left(Q_{ij}.(1-\alpha).\beta\right) + \left(Q_{ij}(1-\alpha).(1-\beta).\gamma\right)\right]$$

$s.t.$

$$\sum_{j}^{m}\sum_{i}^{n}\left[\left(Q_{ij}.f_m\right) + \left(\frac{D_{ij}}{Q_{ij}}.L_j.f_t\right) + \left(Q_{ij}.D_{ij}.f_k\right)\right] \leq Cap_j$$

$$\sum_{j}^{m}\sum_{i}^{n} C_i.Q_{ij}(1-\alpha) \leq B_j + \left(B_j^-\right)$$

$$\sum_{j}^{m}\sum_{i}^{n}\left(Q_{ij}(1-\alpha) - b_{ij}\right) \leq F_j$$

$$V_i \leq Q_{ij} \leq W_i$$

$$\sum_{i}^{n}\sum_{j}^{m} Q_{ij} \leq G$$

$$\sum_{i}^{n}\sum_{j}^{m}\frac{D_{ij}}{Q_{ij}} \leq N$$

$$b_{ij} \leq Q_{ij}$$

$$Q_{ij} > 0, integer, i = 1,2,\dots,n$$

$$b_{ij} \geq 0, integer, j = 1,2,\dots,m$$

$$B_j^- \geq 0, \qquad (7.16)$$

In this non-exergy sustainable model, we are looking to optimize three objectives simultaneously: the total inventory cost, the entire cost associated with the additional required budget of all buyers, and the penalty cost of coal waste disposal to the environment. Consequently, we have three decision variables, for example, the amount of required loan (more budget) for each buyer (B_j^-), order quantity of each item for each buyer (Q_{ij}), and amount of backorder of each item for each buyer (b_{ij}).

7.2. The inventory model in fuzzy environment

This subsection is the same as fuzzy environmental issues in chapter 5.

7.3. Exergy Modeling of fuzzy optimization of SVMB coal SC under VMI

This subsection is the same as Exergy Modeling in chapter 5.

7.3.1 A fuzzy exergy Modeling of coal SC with carbon cap policy

As a result, by employing the exergy formulas to the objective functions and limitations of model in Eq. (7.16), it is converted to fuzzy exergy models under carbon cap as follows:

$$TC_{(x)cap} = \sum_{i}^{n}\sum_{j}^{m}\Bigg[\frac{\widetilde{D_{ij}}}{Q_{ij}}\big(A_{(x)i,s} + A_{(x)ij,b}\big) + \frac{h_{(x)ij}}{2Q_{ij}}\big(Q_{ij}(1-\alpha) - b_{ij}\big)^2 + \left(\frac{s_{(x)1}.\,b_{ij}^2}{2Q_{ij}} + \frac{s_{(x)2}.\,b_{ij}.\,\widetilde{D_{ij}}}{Q_{ij}}\right) + \frac{\widetilde{D_{ij}}}{Q_{ij}}\big(A_{(x)ij,t}\big)\Bigg] + \sum_{j}^{m}\big[B_{(x)j}^{-} + \big(int^{-} \times B_{(x)j}^{-}\big)\big] + C_{(x)waste} \times \sum_{i}^{n}\sum_{j}^{m}\big[\big(Q_{ij}.\,\alpha\big) + \big(Q_{ij}.\,(1-\alpha).\,\beta\big) + \big(Q_{ij}(1-\alpha).\,(1-\beta).\,\gamma\big)\big]$$

$s.t.$

$$\sum_{i}^{n}\sum_{j}^{m}\left[\big(Q_{ij}.\,f_m\big) + \left(\frac{\widetilde{D_{ij}}}{Q_{ij}}.\,L_j.\,f_t\right) + \big(Q_{ij}.\,\widetilde{D_{ij}}.\,f_k\big)\right] \leq Cap_j$$

$$\sum_{j}^{m}\sum_{i}^{n} C_{(x)i}.\,Q_{ij}(1-\alpha) \leq B_{(x)j} + \big(B_{(x)j}^{-}\big)$$

$$\sum_{j}^{m}\sum_{i}^{n}\big(Q_{ij}(1-\alpha) - b_{ij}\big) \leq F_j$$

$$V_i \leq Q_{ij} \leq W_i$$

$$\sum_{i}^{n}\sum_{j}^{m} Q_{ij} \leq \tilde{G}$$

$$\sum_{i}^{n}\sum_{j}^{m}\frac{\widetilde{D_{ij}}}{Q_{ij}} \leq N$$

$$b_{ij} \leq Q_{ij}$$

$$Q_{ij} > 0, integer, i = 1,2,\ldots,n$$

$b_{ij} \geq 0, integer, j = 1,2, \dots, m$

$$B^{-}_{(x)j} \geq 0, \tag{7.17}$$

7.4. Solution method

This section is the same as the chapter 5 with the same methods and metaheuristic algorithms.

7.5. Numerical examples

This section is the same as the chapter 5 with the same real case study in Iran and all test problems.

7.5.1 Solving phases and related results

To avoid complexity of the chapter, the results of each phase of solving procedure for all test problems include Tables and Figures are presented in Appendix 1.

Table 7.1. Sensitivity analysis of exergy components under carbon cap and tax policies (Fuzzy total exergy in MJ)

Country	Policy	Set A(30-60-10)	Set B(50-30-20)	Set C(20-50-30)	Set D(30-20-50)	Set E(33-33-33)	Minimum (MJ)	Maximum (MJ)
Afghanistan	**Cap**	141,316.53	164,919.79	146,451.08	174,187.82	161,779.26	141,316.53	174,187.82
	Tax	1,504,757.85	1,533,788.62	1,533,954.88	1,512,552.55	1,540,156.67	1,504,757.85	1,540,156.67
Canada	**Cap**	3,269,610.51	1,285,976.37	3,268,083.12	666,924.42	1,555,685.52	666,924.42	3,269,610.51
	Tax	4,606,147.99	2,667,490.61	4,606,446.58	2,055,844.41	3,007,167.24	2,055,844.41	4,606,446.58
Germany	**Cap**	3,216,971.32	1,192,900.68	3,048,417.64	600,277.13	1,528,691.42	600,277.13	3,216,971.32
	Tax	4,479,364.93	2,655,420.96	4,492,797.20	2,109,044.72	2,928,353.16	2,109,044.72	4,492,797.20
Iran	**Cap**	734,828.56	854,814.77	761,440.02	901,519.42	838,931.07	734,828.56	901,519.42
	Tax	2,110,974.62	2,230,157.59	2,234,708.24	2,274,445.14	2,220,750.94	2,110,974.62	2,274,445.14
Turkey	**Cap**	2,972,014.13	3,256,774.91	3,032,929.71	3,368,441.83	3,219,102.84	2,972,014.13	3,368,441.83
	Tax	4,351,316.03	4,654,099.79	4,412,490.90	4,780,003.95	4,602,880.36	4,351,316.03	4,780,003.95
Min. (MJ)	**Cap**	**141,316.53**	**164,919.79**	**146,451.08**	**174,187.82**	**161,779.26**		
	Country	**AF**	**AF**	**AF**	**AF**	**AF**		
	Tax	**1,504,757.85**	**1,533,788.62**	**1,533,954.88**	**1,512,552.55**	**1,540,156.67**		
	Country	**AF**	**AF**	**AF**	**AF**	**AF**		
Max. (MJ)	**Cap**	**3,269,610.51**	**3,256,774.91**	**3,268,083.12**	**3,368,441.83**	**3,219,102.84**		
	Country	**CA**	**TR**	**CA**	**TR**	**TR**		
	Tax	**4,606,147.99**	**4,654,099.79**	**4,606,446.58**	**4,780,003.95**	**4,602,880.36**		
	Country	**CA**	**TR**	**CA**	**TR**	**TR**		

7.6 Comparing the carbon cap and tax policies

All sensitivity analysis results under carbon cap and tax policies are integrated in Table 7.1. Considering the results of Chapters 5 and this chapter, comparing the results of coal SCs under carbon cap and tax policies in developed and developing countries include Afghanistan, Canada, Germany, Iran and Turkey is possible. Generally, if we consider all inventory costs parameter the same, the total exergy (MJ) of coal SC under carbon tax policy is higher than carbon cap policy since there is an additional tax cost in the objective function of the model (see Chapter 5, Eq. 5.9).

7.6.1 Analysis of each country-carbon cap and tax policies

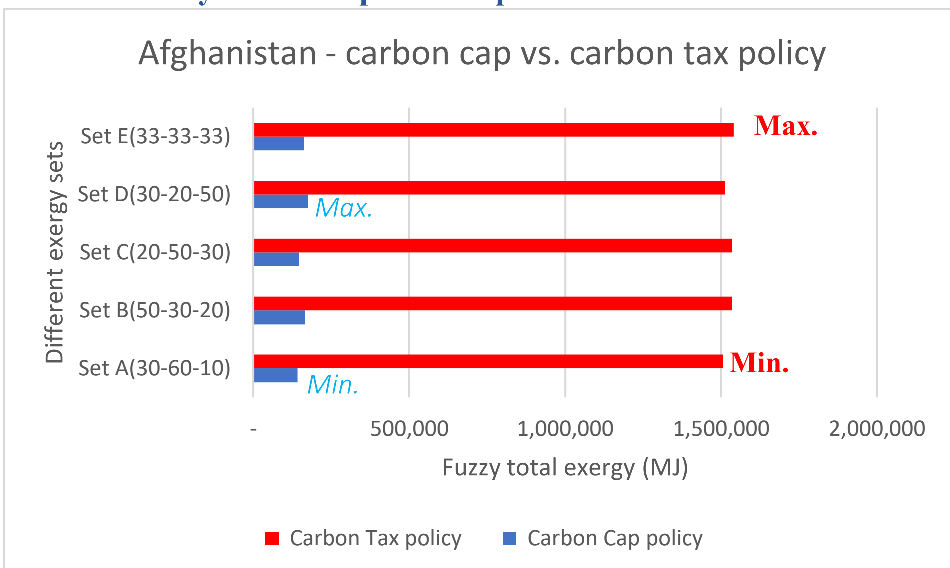


Fig. 7.1. Sustainability of coal SC in Afghanistan under the carbon cap and tax policies

- **Afghanistan** (Fig. 7.1): in this developing country, the best sustainability performance of coal SC under both carbon cap and tax policies are with exergy Set A (30-60-10) since more exergy weight is assigned for Labor (60%) and less for Environment (10%). It created the minimum fuzzy total exergy of 141,316.53 and 1,504,757.85 (MJ) for coal SC by carbon cap and tax policies, respectively. Furthermore, exergy Set E (33-33-33) creates the worst sustainability performance in Afghanistan under both carbon cap and tax policies since the same weights (33%) are assigned to Capital, Labor, and Environment elements.

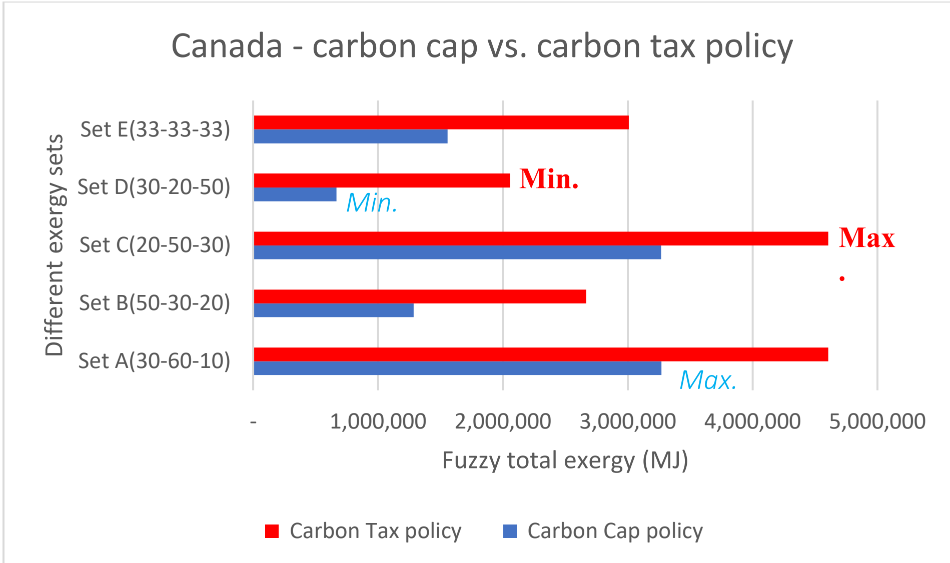


Fig. 7.2. Sustainability of coal SC in Canada under the carbon cap and tax policies

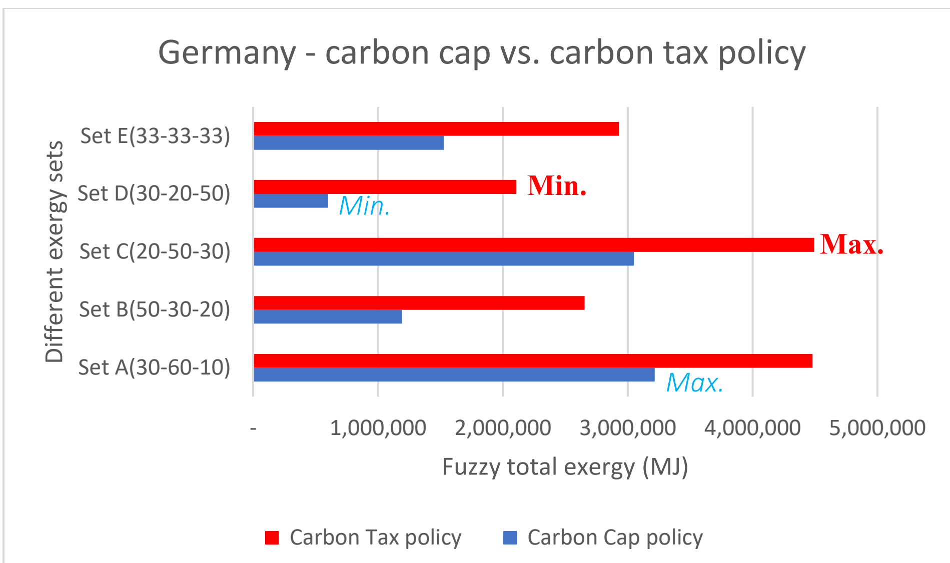


Fig. 7.3. Sustainability of coal SC in Germany under the carbon cap and tax policies

- **Canada** (Fig. 7.2): in this developed country, the top sustainability performance of coal SC under both carbon cap and tax policies are with exergy Set D (30-20-50) when Environment has 50% weight, going along with Capital (30%) and Labor (20%), respectively. It created the minimum fuzzy total exergy of 666,924.42 & 2,055,844.41 (MJ) for coal SC by carbon cap and tax policies, respectively. Moreover, under carbon cap policy, this is exergy Set A (30-60-10) which creates the worst sustainability performance whereas only 10% is assigned to Environmental element. Under carbon tax policy, exergy Set C (20-50-30) makes the worst sustainability performance in Canada when more exergy weight is supposed for Labor (50%).

- **Germany** (Fig. 7.3): Like Canada, exergy Set D (30-20-50) with 50% Environmental weight creates the best sustainability performance under both carbon cap and tax policies. It produced the minimum fuzzy total exergy of 600,277.13 & 2,109,044.72 (MJ) for coal SC in Germany by carbon cap and tax policies, respectively. Likewise, under carbon cap policy, this is exergy Set A (30-60-10) which creates the worst sustainability performance whereas only 10% is assigned to Environmental element. Under carbon tax policy, exergy Set C (20-50-30) with 50% Labor weight makes the lowest sustainability performance.

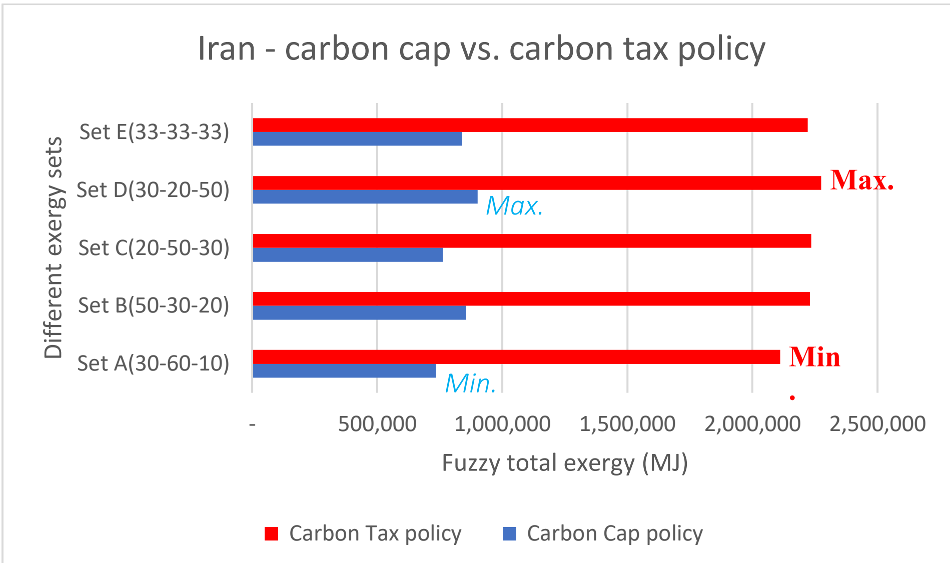


Fig. 7.4. Sustainability of coal SC in Iran under the carbon cap and tax policies

- **Iran** (Fig. 7.4): In this developing country, the highest sustainability performance of coal SC is by exergy Set A (30-60-10), as Labor has 60% while Environment has only 10%. It made the minimum fuzzy total exergy of 734,828.56 & 2,110,974.62 (MJ) under both carbon cap and tax policies. The lowest sustainability performance is with exergy Set D (30-20-50), when 50% weight is allocated to Environment, which created the maximum fuzzy total exergy (MJ) under both carbon policies.

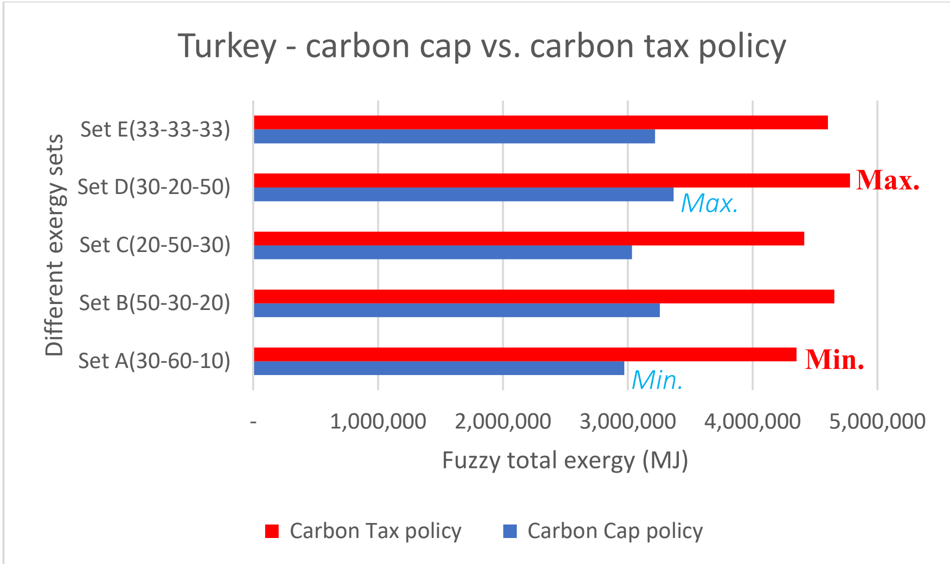


Fig. 7.5. Sustainability of coal SC in Turkey under the carbon cap and tax policies

- **Turkey** (Fig. 7.5): This developing country has the same sustainability conditions with Iran. the best sustainability performance is with exergy Set A (30-60-10), while more exergy percentage is given to Labor (60%). It established the minimum amount of fuzzy total exergy with 2,972,014.13 & 4,351,316.03 (MJ) by carbon cap and tax policies, respectively. Similarly, the maximum fuzzy total exergy (the lowest sustainability in MJ) is with exergy Set D (30-20-50) when more weight is provided to the Environment (50%).

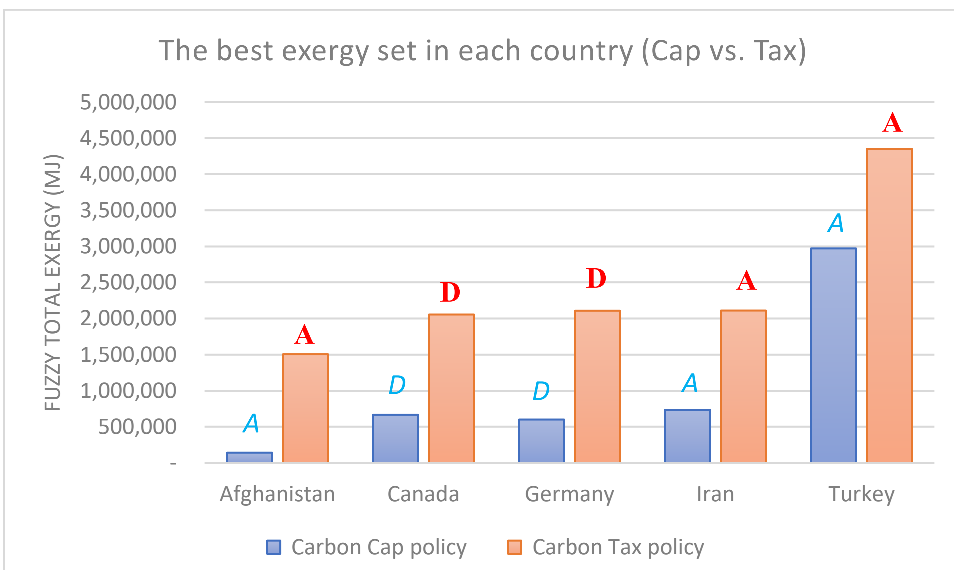


Fig. 7.6. The best exergy set for each country under the carbon cap and tax policies

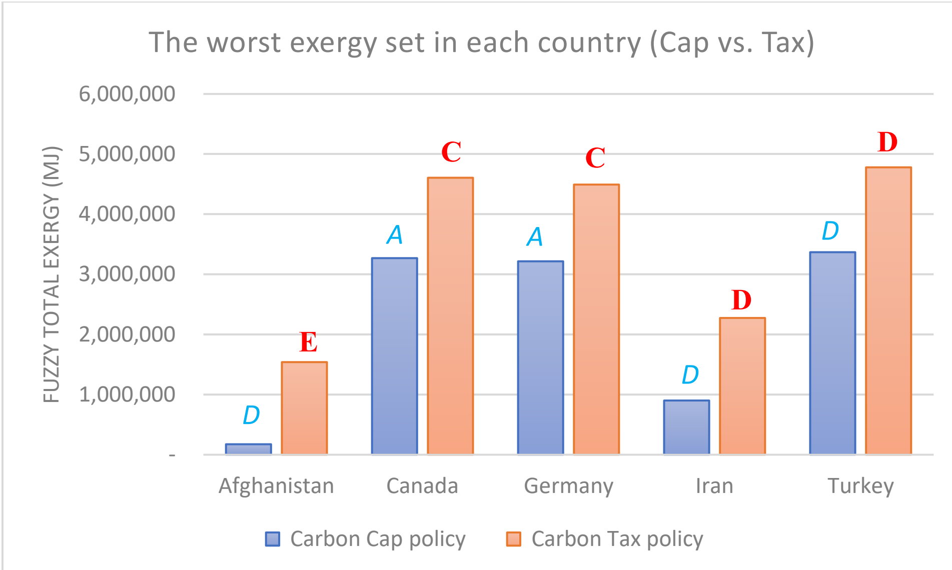


Fig. 7.7. The worst exergy set for each country under the carbon cap and tax policies

- Respecting Fig. 7.6, the best exergy set in developing countries like Afghanistan, Iran and Turkey is exergy Set A (30-60-10) under both carbon cap and tax policies, while more exergy percentage is given to Labor (60%). It creates the highest sustainability conditions with the lowest fuzzy total exergy in MJ. Moreover, in developed countries like Canada and Germany, the best exergy set is Set D (30-20-50) with 50% Environmental weight creates the best sustainability performance under both carbon cap and tax policies.
- Among all presented developed and developing countries, the coal SC in Afghanistan has the lowest total exergy (the most sustainable conditions) with 141,316.53 & 1,504,757.85 (MJ) under carbon cap and tax policies, respectively (see Fig. 7.6). Germany, Canada, Iran, and Turkey are followed Afghanistan.
- Respecting Fig. 7.7, the worst exergy set in developing countries like Iran and Turkey is Set D (30-20-50) with 50% Environmental weight. It creates the highest fuzzy total exergy (the lowest sustainability) under both carbon cap and tax policies. In developed countries such as Canada and Germany, the worst exergy set under the carbon cap policy is Set A (30-60-10) and under carbon tax policy is Set C (20-50-30) with 50% Labor weight.
- Moreover, coal SC in Turkey has the highest fuzzy total exergy (the lowest sustainability conditions) among all presented developed and developing countries with 3,368,441.83 & 4,780,003.95 (MJ) under carbon cap and tax policies, respectively (see Fig. 7.7).

7.6.2 Analysis of each exergy set-carbon cap and tax policies

Considering Table 7.1 for each exergy set, we have:

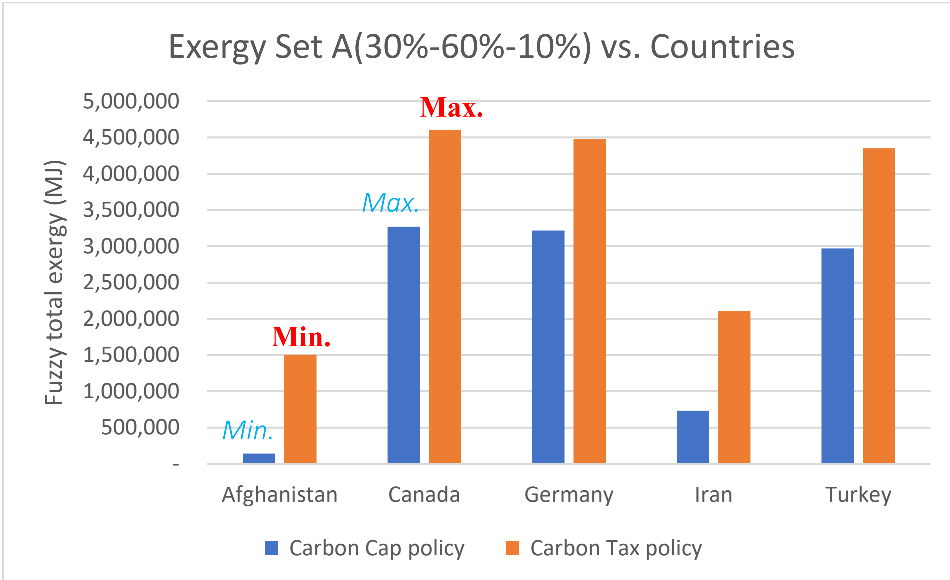


Fig. 7.8. The exergy Set A in developed and developing countries under the carbon cap and tax policies.

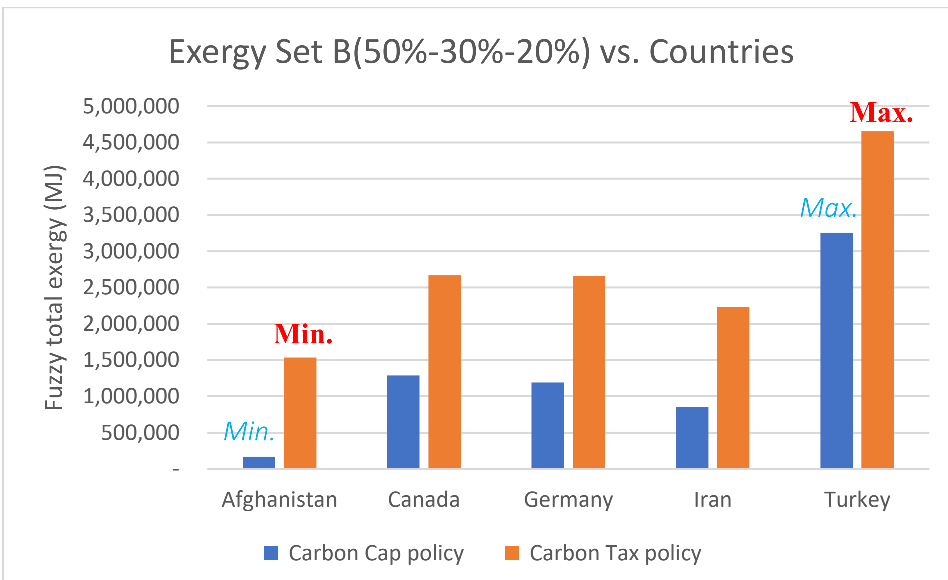


Fig. 7.9. The exergy Set B in developed and developing countries under the carbon cap and tax policies.

- **Exergy Set A (30%-60%-10%):** Considering this exergy set which has 60% weight for Labor (60%) and only 10% to Environment, creates the most sustainable performance (the lowest fuzzy total exergy in MJ) in Afghanistan under both carbon cap and tax policies. At the same time, exergy set A creates the worst sustainability performance with highest fuzzy total exergy (MJ) in Canada under both carbon policies (see Fig. 7.8).
- **Exergy Set B (50%-30%-20%):** Regarding this exergy set which has more emphasis on Capital (50%), coal SC in Turkey has the lowest sustainability performance (the highest fuzzy total exergy in MJ) under both carbon policies. At the same time, exergy set B works well in Afghanistan (see Fig. 7.9).

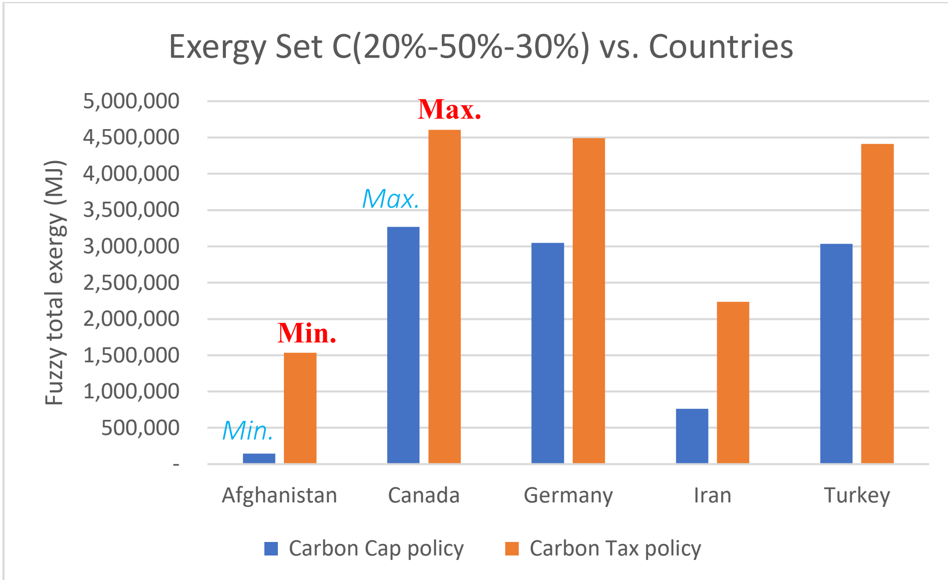


Fig. 7.10. The exergy Set C in developed and developing countries under the carbon cap and tax policies.

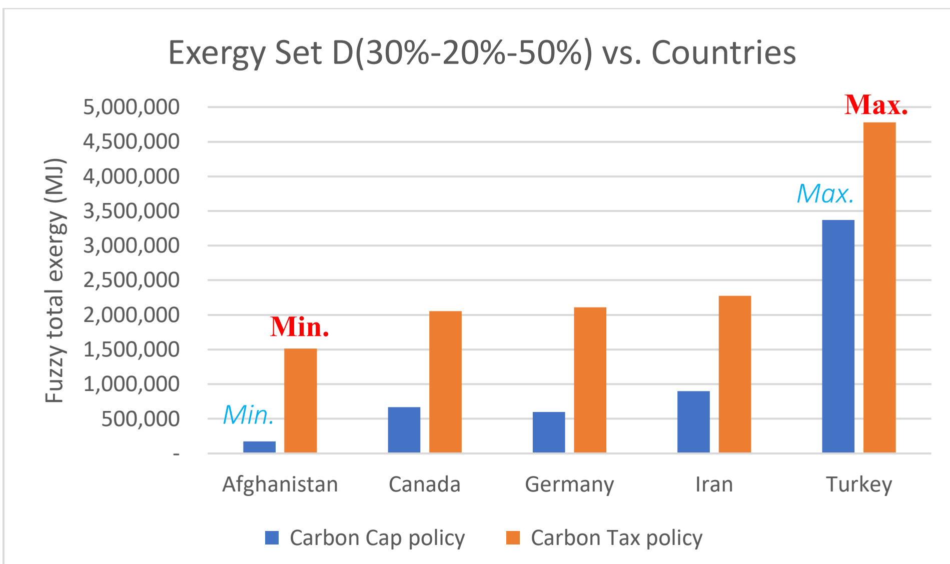


Fig. 7.11. The exergy Set D in developed and developing countries under the carbon cap and tax policies.

- **Exergy Set C (20%-50%-30%):** In this exergy set is assigned more weight on Labor (50%) which creates the best sustainability conditions for coal SC in Afghanistan under both carbon policies. Simultaneously, it creates the lowest sustainability conditions in Canada (see Fig. 7.10).
- **Exergy Set D (30%-20%-50%):** When more emphasis is put on Environment (50%), exergy set D creates the worst sustainability conditions in Turkey under both carbon cap and tax policies. All at once, it operates well in terms of sustainability in Afghanistan (see Fig. 7.11).

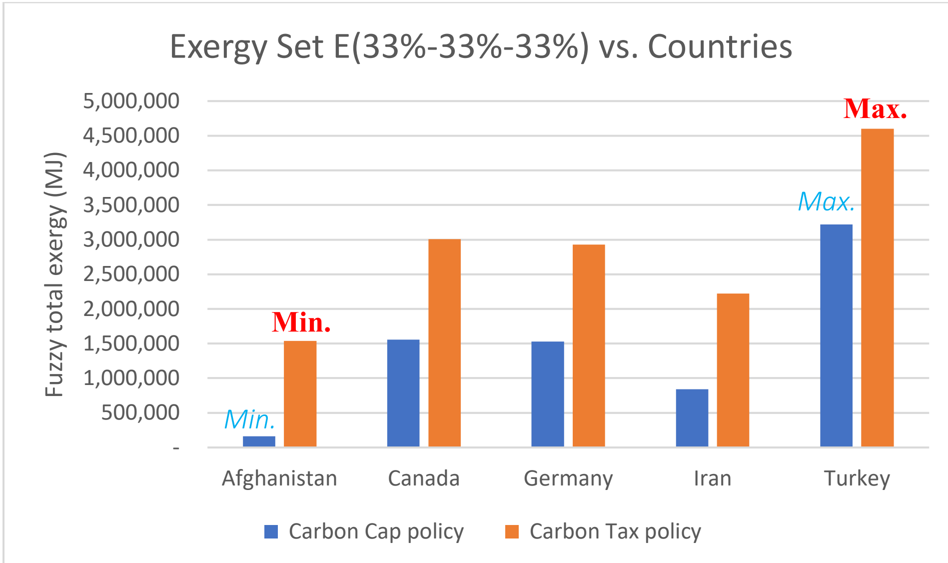


Fig. 7.12. The exergy Set E in developed and developing countries under the carbon cap and tax policies.

- **Exergy Set E (33%-33%-33%):** In this set, all three exergy components have equal 33% weight which creates the highest fuzzy total exergy (the lowest sustainability) in Turkey and the lowest in Afghanistan under both carbon cap and tax policies (see Fig. 7.12).
- Moreover, all exergy Sets (A-E) generated the minimum fuzzy total exergy for coal SC in Afghanistan among all presented countries.

In this chapter, carbon cap policy is applied to the EOQ model in Chapter 5 to make a comparison between using the carbon tax and cap policies in terms of Joules in a coal SC among five developed and developing countries such as Afghanistan, Canada, Germany, Iran and Turkey. All sensitivity results are presented in Table 7.1 for coal SC in five countries. Moreover, analysis of each country (subsection 7.6.1) and analysis of each exergy set (subsection 7.6.2) for both carbon tax and cap policies are presented in this chapter. In the next chapter, carbon offset policy will be applied to the coal SC.

CHAPTER 8. ADDITIONAL RESULTS FOR CHAPTER 6

Forewords

Previous chapters considered carbon tax, trade, and cap policies for coal SC. Now, this chapter follows Chapter 6 while considers carbon offset policy to improve the sustainability of coal SC in both developed and developing countries by extended exergy accounting.

Similar to the concept of Chapter 7, in this Chapter carbon offset policy is applied to the EPQ model of the coal SC in Chapter 6 (under carbon trade policy) and then the model is converted to a sustainable coal SC (in terms of Joules) by using EEA method. To make a comparison between the results of the EPQ model under carbon trade and offset policies, the same assumptions, and concepts (as Chapter 6) are used here.

The following subsections will develop a non-exergy EPQ model of the coal SC for carbon offset policy. Then the model is converted to an exergy fuzzy model by applying the EEA method.

8.1. A non-exergy Modeling of coal SC with carbon offset policy

8.1.1. Objective function

A carbon offset is a product or service that a company buys or invests in in order to cut its carbon emissions. Companies regularly pay third-party companies to absorb additional carbon emissions by planting trees or developing green environmental protection plans (Fisher et al., 2018). In the carbon offset plan, companies are given a carbon agreement goal, and carbon further than the goal is offset by buying carbon credits (e^+, as a decision variable) from qualified emission decrease sources (Zhou and Wen 2019). The distinction between carbon offset and carbon trade is that companies need to buy the carbon credits with the carbon offset policy. In contrast, the surplus carbon credits cannot be sold (Li et al., 2020). Although the price of carbon is considered known and fixed in the literature, this study considers it fuzzy. If the company's carbon surpasses the given carbon limit, they must pay carbon offset cost for additional carbon credits ($C_{offset} \times e^+$), which is an objective function for the model. Consequently, the carbon offset cost is

$$Z_1 = \sum_{j}^{m} C_{offset} \times \left(e_j^+\right) \tag{8.1}$$

The shipping costs accounted for about 40% of the entire delivered cost of coal in 2019 (U.S. Energy Information Administration (EIA), 2019). Transportation costs are also impacted by road distance, accessibility of shipping mode and supply source alternatives, and the competition among coal and other goods for shipping. Therefore, the total transportation cost of coal includes constant (t_f) and variable (t_v) costs, along with the cost of loading/unloading coal (t_L) in/from railcars and cost of equipment (t_M) is

$$Z_2 = \sum_{i}^{n}\sum_{j}^{m}\left[\left(\frac{D_{ij}}{Q_{ij}}.t_f\right) + \left(Q_{ij}.t_v\right) + \left(\frac{D_{ij}}{Q_{ij}}.(Lo + Un).(t_L + t_M)\right)\right] \qquad (8.2)$$

Where (Lo, Un) are the loading/unloading time of coal in/from a railcar. The vendor-managed inventory (VMI) strategy is the regular inventory management in SC in which the upstream company completely controls the inventory at the downstream company's location (Giovanni, 2021). In the VMI system, the determinations about scheduling and amount of buyer's replenishment are decided by the supplier that is assumed to have comprehensive information concerning the customers' requirements, to prevent stockouts (Çomez-Dolgan et al., 2021, Maio and Lagana, 2020). Therefore, it is expected that the supplier gives the ordering, shipping, and keeping costs rather than the buyer as a part of the stated contract; the buyer gives no cost (Mateen et al., 2014; Yao et al., 2007; Razmi et al., 2010; Pasandideh et al., 2011; Roozbeh Nia et al., 2014, 2015). Furthermore, in an EPQ model with defective quality items and stockout as a backorder that utilizes the VMI strategy, the coal SC's total inventory cost is established by calculating the ordering/setup $(TC_{O_{ij}})$, keeping $(TC_{H_{ij}})$, stockout $(TC_{S_{ij}})$, and purchasing $(TC_{P_{ij}})$ costs as (Pasandideh et al., 2010, 2011)

$$Z_3 = TC_{O_{ij}} + TC_{H_{ij}} + TC_{S_{ij}} + TC_{P_{ij}} \qquad (8.3)$$

Where,

$$TC_{O_{ij}} = \sum_{i}^{n}\sum_{j}^{m}\frac{D_{ij}}{Q_{ij}}\left(K_{i,s} + K_{ij,b}\right) \qquad (8.4)$$

$$TC_{H_{ij}} = \sum_{i}^{n}\sum_{j}^{m}\frac{h_{ij}}{2Q_{ij}\left(1-\frac{D_{ij}}{P_i}\right)}\left(Q_{ij}(1-\delta_m)\left(1-\frac{D_{ij}}{P_i}\right) - b_{ij}\right)^2 \qquad (8.5)$$

$$TC_{S_{ij}} = \sum_{i}^{n}\sum_{j}^{m}\left(\frac{s_1.b_{ij}^2}{2Q_{ij}\left(1-\frac{D_{ij}}{P_i}\right)} + \frac{s_2.b_{ij}.D_{ij}}{Q_{ij}\left(1-\frac{D_{ij}}{P_i}\right)}\right) \qquad (8.6)$$

$$TC_{P_{ij}} = \sum_{i}^{n}\sum_{j}^{m}C_i.D_{ij} \qquad (8.7)$$

Where (D_{ij}, Q_{ij}, h_{ij}) are the demand rate, order quantity and holding cost per unit of coal *i* for buyer *j,* respectively. As mentioned previously, the existing budget of each buyer could be deposited in a bank account or invested in other projects to get profits. Now, we take into account a real-world balanced limitation where the total amount of the existing budget for each buyer is restricted (see Eq. 8.8). To the best of the authors' knowledge, this type of objective function and limitation, have not been studied yet. On the one hand, each buyer's under-achievement budget (x_j^+ as a decision variable) is regarded as the benefit. It means this amount of money (x_j^+) may be invested in a new project with an actual interest rate (int^+) and make a profit (as a $int^+ \times x_j^+$) for the buyer. On the other hand, the over-achievement budget (x_j^- as a decision variable) is regarded as the cost. It means the buyer must get a loan with the amount of (x_j^-) and an interest rate of (int^-). After All, the buyer should pay this loan as well as the interest rate ($x_j^- + [int^- \times x_j^-]$) at the end of the period. Therefore, the total cost/benefit associated with the budget of all buyers is

$$Z_4 = \sum_{j}^{m} [x_j^- + (int^- \times x_j^-) - (int^+ \times x_j^+)] \tag{8.8}$$

Wherever in Eq. (8.8), the first two components are linked to the cost functions, and the last part with a negative symbol is related to the benefit obtained. Moreover, under and over-achievement budgets (x_j^+, x_j^-) are not known parameters and are considered decision variables. Hence, the non-exergy total cost of coal SC under the carbon offset policy is the summation of $TC_{offset} = Z_1 + Z_2 + Z_3 + Z_4$.

8.1.2. The constraints

The constraints of this model are as follows:

$$\frac{\sum_i^n \sum_j^m C_0 \,.\, D_{ij}}{\sum_i^n \sum_j^m \dfrac{C_0.\left(Q_{ij}(1-\delta_m)\left(1-\frac{D_{ij}}{P_i}\right)-b_{ij}\right)^2}{2Q_{ij}\left(1-\frac{D_{ij}}{P_i}\right)}} \geq ITR_{\,j} \tag{8.9}$$

$$\sum_{i}^{n} \left[(Q_{ij}.\theta_m) + \left(\frac{D_{ij}}{Q_{ij}}.L_j.\theta_t\right) + (Q_{ij}.D_{ij}.\theta_k) \right] \leq E_j + (e_j^+) \tag{8.10}$$

$$\sum_{i}^{n}\sum_{j}^{m} [(Q_{ij}.\delta_m) + (Q_{ij}.(1-\delta_m).\delta_t) + (Q_{ij}(1-\delta_m).(1-\delta_t).\delta_k)] \leq F \tag{8.11}$$

$$\sum_{i}^{n} \left[Q_{ij}(1-\delta_m)\left(1-\frac{D_{ij}}{P_i}\right) - b_{ij} \right] \leq W_j \tag{8.12}$$

$$\sum_{i}^{n} [C_i.Q_{ij}(1-\delta_m)] + (x_j^+ - x_j^-) = X_j \tag{8.13}$$

$$\sum_{i}^{n}\sum_{j}^{m} \frac{D_{ij}}{Q_{ij}} \leq N_{Max} \tag{8.14}$$

$$Q_{ij} \leq Q_{Max} \tag{8.15}$$

$$b_{ij} \leq Q_{ij} \tag{8.16}$$

Eq. (8.9) is an inventory turnover ratio ($ITR_{\,j}$) limitation. To the best of the authors' knowledge, this limitation has not been presented in SC literature before. The inventory turnover ratio is applied as a comparative measure of inventory performance between competitors and is crucial to control inventory (Beklari et al., 2018). This proportion is an economic index that merges the cost of goods sold with average inventories at cost (Kwak 2019). The inventory turnover ratio shows how often inventories are turned over a period. For Eq. (8.10), as mentioned before, with the policy of carbon offset, each buyer inside coal SC can only produce within an offered cap (E_j) of emission. If this actual emission amount goes above the emission limit, the company must purchase carbon credits (e^+) (Li et al., 2020). Hence, with the emission offset policy, a new emission restriction is included in the model where Eq. (8.10) corresponds to the total generated carbon in mining, shipping, and steelmaking processes. In Eq. (8.10), ($\theta_m, \theta_t, \theta_k$) are emissions factors in mining, transportation, and steel manufacturer processes, respectively. Additionally, L_j is the distance between the coal vendor and buyer j. Eq. (8.11) aims to make the model green since it considers a limitation (F) on total defective products (waste) disposal to the environment by all processes in coal SC. In this equation, ($\delta_m, \delta_t, \delta_k$) are the proportions of imperfect quality items in mining, transportation, and steel manufacturer processes, respectively. Furthermore, Eq. (8.12) expresses that the warehouse space of each buyer (W_j) is restricted, where (b_{ij}) is the backorder amount of coal i for buyer j in a cycle (a decision variable).

As shown before, a real-world contractual agreement grants balanced constraints (Eq. 8.13) for the existing budget of each buyer (X_j). To the best of the authors' knowledge, this type of limitation has not been given in the SC literature in the past. Where Eq. (8.13) indicates that, on the one hand, if the total paid-out money of a buyer is below the existing budget ($\sum_i^n C_i . Q_{ij}(1-\delta_m) < X_j$), the buyer saves an amount of ($x_j^+ > 0$). It is possible the company invests this amount in a new project and makes a profit (see Eq. 6.8). On the other hand, if the total paid out money of a buyer is more than the existing budget ($\sum_i^n C_i . Q_{ij}(1-\delta_m) > X_j$), so the buyer demands to get a loan with the amount of ($x_j^- > 0$). The total cost/benefit linked to this balanced limitation is expressed in Eq. (8.8). In addition, Eq. (8.14) is related to the limitation on the total number of orders (N_{Max}) by all buyers. Additionally, there is a constraint for the shipping system (railway) while the Max. of shipping capacity (Q_{Max}) for each order quantity is stated in Eq. (8.15).

Finally, based on Eq. (8.16), the quantity of backorder of product i for j^{th} buyer (b_{ij}) in a cycle should be fewer than or equal to its order amount (Q_{ij}). It should be mentioned that intending to simplify the mathematical model; we ignore the cost of purchasing (Eq. 8.7) in our model. Regarding Eqs. (8.1)-(8.16) and under carbon offset policy, the non-exergy crisp model of "multi-product" balanced limitations single-vendor multi-buyer (SVMB) EPQ can be easily achieved as

$$TC_{offset} = \sum_i^n \sum_j^m \left[\frac{D_{ij}}{Q_{ij}} (K_{i,s} + K_{ij,b}) + \frac{h_{ij}}{2Q_{ij}\left(1-\frac{D_{ij}}{P_i}\right)} \left(Q_{ij}(1-\delta_m)\left(1-\frac{D_{ij}}{P_i}\right) - b_{ij} \right)^2 + \left(\frac{s_1 . b_{ij}^2}{2Q_{ij}\left(1-\frac{D_{ij}}{P_i}\right)} + \frac{s_2 . b_{ij} . D_{ij}}{Q_{ij}\left(1-\frac{D_{ij}}{P_i}\right)} \right) \right] + \sum_j^m C_{offset} \times (e_j^+)$$

$$+\sum_{j}^{m}\left[x_j^- + \left(int^- \times x_j^-\right) - \left(int^+ \times x_j^+\right)\right]$$

$$+\sum_{i}^{n}\sum_{j}^{m}\left[\left(\frac{D_{ij}}{Q_{ij}}.t_f\right) + \left(Q_{ij}.t_v\right) + \left(\frac{D_{ij}}{Q_{ij}}.(Lo + Un).(t_L + t_M)\right)\right]$$

$s.t.$

$$\frac{\sum_i^n \sum_j^m C_0 \,.\, D_{ij}}{\sum_i^n \sum_j^m \frac{C_0.\left(Q_{ij}(1-\delta_m)\left(1-\frac{D_{ij}}{P_i}\right) - b_{ij}\right)^2}{2Q_{ij}\left(1-\frac{D_{ij}}{P_i}\right)}} \geq ITR_j$$

$$\sum_{i}^{n}\left[\left(Q_{ij}.\theta_m\right) + \left(\frac{D_{ij}}{Q_{ij}}.L_j.\theta_t\right) + \left(Q_{ij}.D_{ij}.\theta_k\right)\right] \leq E_j + (e_j^+)$$

$$\sum_{i}^{n}\sum_{j}^{m}\left[\left(Q_{ij}.\delta_m\right) + \left(Q_{ij}.(1-\delta_m).\delta_t\right) + \left(Q_{ij}(1-\delta_m).(1-\delta_t).\delta_k\right)\right] \leq F$$

$$\sum_{i}^{n}\left(Q_{ij}(1-\delta_m)\left(1-\frac{D_{ij}}{P_i}\right) - b_{ij}\right) \leq W_j$$

$$\sum_{i}^{n} C_i.\,Q_{ij}(1-\delta_m) + \left(x_j^+ - x_j^-\right) = X_j$$

$$\sum_{i}^{n}\sum_{j}^{m}\frac{D_{ij}}{Q_{ij}} \leq N_{Max}$$

$$Q_{ij} \leq Q_{Max}$$

$$b_{ij} \leq Q_{ij}$$

$$Q_{ij} > 0, integer, i = 1,2,\ldots,n$$

$$b_{ij} \geq 0, integer, j = 1,2,\ldots,m$$

$$x_j^+, x_j^-, e_j^+, e_j^- \geq 0, \tag{8.17}$$

In this non-exergy sustainable model, we are looking to optimize four objectives simultaneously: (a) the total inventory cost, (b) the entire cost associated with the additional required budget of all buyers, (c) the total coal transportation cost among SC members, (d) and the cost of produced carbon emission by all processes. Consequently, we have five decision variables, for example, the amount of required loan/investment for each buyer (x_j^-, x_j^+), the carbon credits for each buyer (e_j^+), the order quantity of each item for each buyer (Q_{ij}), and the amount of backorder of each item for each buyer (b_{ij}). The following subsection considers uncertainty to the non-exergy model in Eq. (8.17).

8.2. The inventory model in fuzzy environment

This subsection is the same as fuzzy environmental issues in chapter 6.

8.3. Exergy modeling of fuzzy optimization of SVMB coal SC under VMI

This subsection is the same as Exergy Modeling in Chapter 6.

8.3.1 A fuzzy exergy Modeling of coal SC with carbon offset policy

As a result, by employing the exergy formulas to the objective functions and limitations of model in Eq. (8.17), it is converted to fuzzy exergy models under carbon offset as follows:

$$TC_{(x)offset} = \sum_{i}^{n}\sum_{j}^{m}\left[\frac{\widetilde{D_{ij}}}{Q_{ij}}\left(K_{(x)i,s}+K_{(x)ij,b}\right)+\frac{h_{(x)ij}}{2Q_{ij}\left(1-\frac{\widetilde{D_{ij}}}{P_i}\right)}\left(Q_{ij}(1-\delta_m)\left(1-\frac{\widetilde{D_{ij}}}{P_i}\right)-b_{ij}\right)^2\right.$$
$$\left.+\left(\frac{s_{(x)1}.b_{ij}^2}{2Q_{ij}\left(1-\frac{\widetilde{D_{ij}}}{P_i}\right)}+\frac{s_{(x)2}.b_{ij}.\widetilde{D_{ij}}}{Q_{ij}\left(1-\frac{\widetilde{D_{ij}}}{P_i}\right)}\right)\right]+\sum_{j}^{m}\widetilde{C_{(x)trade}}\times\left(e_j^+\right)$$
$$+\sum_{j}^{m}\left[x_{(x)j}^{-}+\left(int^{-}\times x_{(x)j}^{-}\right)-\left(int^{+}\times x_{(x)j}^{+}\right)\right]$$
$$+\sum_{i}^{n}\sum_{j}^{m}\left[\left(\frac{\widetilde{D_{ij}}}{Q_{ij}}.t_{(x)f}\right)+\left(Q_{ij}.t_{(x)v}\right)+\left(\frac{\widetilde{D_{ij}}}{Q_{ij}}.(Lo+Un).\left(t_{(x)L}+t_{(x)M}\right)\right)\right]$$

$s.t.$

$$\frac{\sum_i^n\sum_j^m C_{(x)0}\,.\widetilde{D_{ij}}}{\sum_i^n\sum_j^m\dfrac{C_{(x)0}.\left(Q_{ij}(1-\delta_m)\left(1-\frac{\widetilde{D_{ij}}}{P_i}\right)-b_{ij}\right)^2}{2Q_{ij}\left(1-\frac{\widetilde{D_{ij}}}{P_i}\right)}}\geq ITR_j$$

$$\sum_{i}^{n}\left[\left(Q_{ij}.\theta_m\right)+\left(\frac{\widetilde{D_{ij}}}{Q_{ij}}.L_j.\theta_t\right)+\left(Q_{ij}.\widetilde{D_{ij}}.\theta_k\right)\right]\leq E_j+\left(e_j^+\right)$$

$$\sum_{i}^{n}\sum_{j}^{m}\left[\left(Q_{ij}.\delta_m\right)+\left(Q_{ij}.(1-\delta_m).\delta_t\right)+\left(Q_{ij}(1-\delta_m).(1-\delta_t).\delta_k\right)\right]\leq F$$

$$\sum_{i}^{n}\left(Q_{ij}(1-\delta_m)\left(1-\frac{\widetilde{D_{\iota J}}}{P_i}\right)-b_{ij}\right)\leq W_j$$

$$\sum_{i}^{n}\left(\widetilde{C_{(x)\iota}}.Q_{ij}(1-\delta_m)\right)+\left(x^{+}_{(x)j}-x^{-}_{(x)j}\right)=X_{(x)j}$$

$$\sum_{i}^{n}\sum_{j}^{m}\frac{\widetilde{D_{\iota J}}}{Q_{ij}}\leq N_{Max}$$

$$Q_{ij}\leq Q_{Max}$$

$$b_{ij}\leq Q_{ij}$$

$$Q_{ij}>0, integer, i=1,2,\dots,n$$

$$b_{ij}\geq 0, integer, j=1,2,\dots,m$$

$$x^{+}_{(x)j}, x^{-}_{(x)j}, e^{+}_{j}, e^{-}_{j}\geq 0, \tag{8.18}$$

8.4. Solution method

This section is the same as the chapter 6 with the same methods and metaheuristic algorithms.

8.5. Numerical examples

This section is the same as the chapter 6 with the same real case study in Iran and all test problems.

8.5.1 Solving phases and related results (carbon offset)

To avoid complexity of the chapter, the results of each phase of solving procedure for all test problems include Tables and Figures are presented in Appendix 2.

8.6 Comparing the carbon trade and offset policies

Considering the results of Chapters 6 and this section, comparing the results of coal SCs under carbon trade and offset policies in some developed and developing countries include Australia, China, India, Iran, Japan, Poland, the USA and Zimbabwe is possible. As mentioned in Chapter 6, these are the countries with high consumption of coal in the world. Table 8.1 presented all sensitivity analysis results under carbon trade and offset policies. Generally, if we consider all inventory costs parameter the same, there is a possibility that total exergy (MJ) of coal SC under carbon trade policy be lower than carbon offset policy since under carbon trade, the company could sell their carbon credits ($Z_1=\sum_j^m C_{trade}\times\left(e_j^{+}-e_j^{-}\right)$) and makes profit (see chapter 6, Eq. 6.1).

Table 8.1. Sensitivity analysis of exergy components under carbon trade and offset policies (Fuzzy total exergy in MJ)

Country	Policy	Set A(30-60-10)	Set B(60-20-20)	Set C(20-50-30)	Set D(20-40-40)	Set E(20-30-50)	Set F(30-10-60)	Set G(33-33-33)	Minimum	Maximum
Australia	**Trade**	37,386,644.58	27,362,603.27	36,172,081.05	30,457,341.89	35,641,776.33	24,251,604.43	33,163,723.31	24,251,604.43	37,386,644.58
	Offset	58,194,888.98	37,972,201.90	29,582,062.77	50,525,851.36	37,058,048.28	25,381,554.37	36,154,500.20	25,381,554.37	58,194,888.98
China	**Trade**	121,884,457.74	109,229,963.03	83,731,242.82	94,201,685.52	111,411,481.62	128,734,240.79	121,351,102.11	83,731,242.82	128,734,240.79
	Offset	178,509,576.98	166,472,938.65	96,953,009.68	156,133,267.82	161,309,694.66	153,294,716.80	136,870,365.31	96,953,009.68	178,509,576.98
India	**Trade**	32,520,676.90	56,664,303.08	24,826,136.13	32,528,308.04	43,026,717.09	29,354,458.87	31,623,790.11	24,826,136.13	56,664,303.08
	Offset	41,297,642.73	58,836,368.81	25,466,158.69	47,301,831.54	45,946,885.83	49,637,349.70	38,479,371.31	25,466,158.69	58,836,368.81
Iran	**Trade**	31,537,292.44	50,042,180.33	35,822,252.13	43,914,327.75	43,802,295.45	49,114,885.31	44,552,827.66	31,537,292.44	50,042,180.33
	Offset	41,699,351.48	76,861,890.52	51,091,655.92	50,771,812.85	48,215,183.84	66,584,735.15	71,932,762.38	41,699,351.48	76,861,890.52
Japan	**Trade**	38,038,472.22	40,279,208.50	30,489,673.91	36,862,147.59	36,228,006.97	22,873,547.02	32,432,070.96	22,873,547.02	40,279,208.50
	Offset	60,286,069.45	40,887,175.47	35,269,221.20	40,123,715.86	38,498,459.38	27,876,026.26	35,790,111.54	27,876,026.26	60,286,069.45
Poland	**Trade**	106,551,302.66	110,155,055.08	86,131,627.76	92,933,114.17	109,302,825.19	123,315,602.00	118,125,544.27	86,131,627.76	123,315,602.00
	Offset	135,055,722.76	156,214,948.54	95,760,363.89	124,452,996.38	135,883,311.16	147,446,020.63	146,622,025.05	95,760,363.89	156,214,948.54
USA	**Trade**	31,673,757.27	22,604,564.59	29,064,237.19	31,090,827.64	25,320,951.45	19,675,609.14	29,934,368.36	19,675,609.14	31,673,757.27
	Offset	38,278,772.24	23,177,067.92	35,476,600.22	39,435,137.75	26,724,522.66	21,032,559.94	33,876,380.99	21,032,559.94	39,435,137.75
Zimbabwe	**Trade**	31,803,458.12	23,779,747.58	26,772,135.64	25,762,854.83	28,886,560.45	22,873,547.02	24,146,338.65	22,873,547.02	31,803,458.12
	Offset	36,156,127.01	25,972,295.09	29,749,298.68	25,914,513.09	33,867,997.48	24,119,890.07	31,260,609.82	24,119,890.07	36,156,127.01
Min. (MJ)	**Trade**	**31,537,292.44**	**22,604,564.59**	**24,826,136.13**	**25,762,854.83**	**25,320,951.45**	**19,675,609.14**	**24,146,338.65**		
	Country	**Iran**	**USA**	**India**	**Zimbabwe**	**USA**	**USA**	**Zimbabwe**		

	Offset	36,156,127.01	23,177,067.92	25,466,158.69	25,914,513.09	26,724,522.66	21,032,559.94	31,260,609.82
	Country	Zimbabwe	USA	India	Zimbabwe	USA	USA	Zimbabwe
Max. (MJ)	Trade	121,884,457.74	110,155,055.08	86,131,627.76	94,201,685.52	111,411,481.62	128,734,240.79	121,351,102.11
	Country	China	Poland	Poland	China	China	China	China
	Offset	178,509,576.98	166,472,938.65	96,953,009.68	156,133,267.82	161,309,694.66	153,294,716.80	146,622,025.05
	Country	China	China	China	China	China	China	Poland

8.6.1 Analysis of each country-carbon trade and offset policies

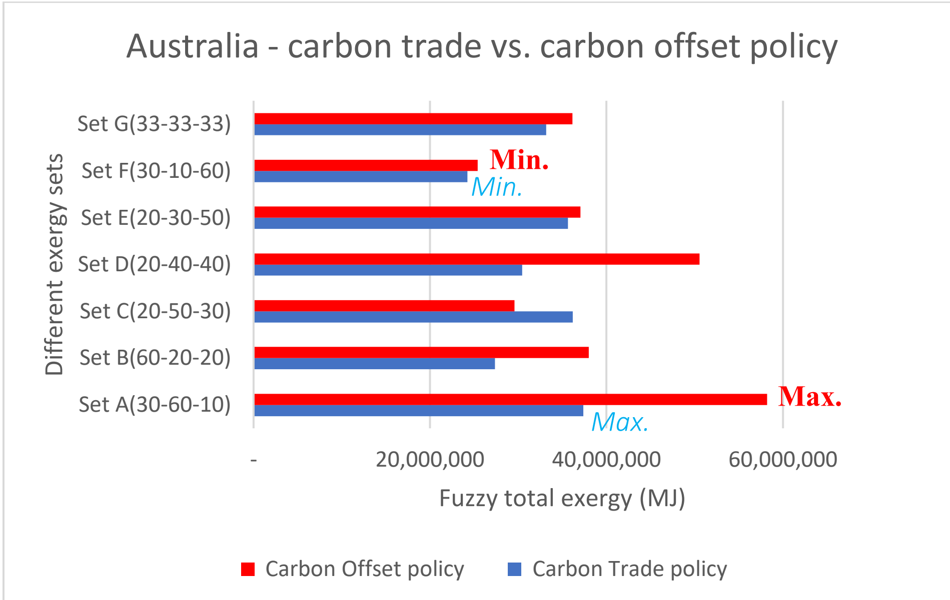


Fig. 8.1. Sustainability of coal SC in Australia under the carbon trade and offset policies

- **Australia** (Fig. 8.1): This developed country is one of the key players in the global coal trade (5.9%). The best sustainability performance of coal SC under both carbon trade and offset policies are with exergy Set F (30-10-60) since more exergy weight is assigned for Environment (60%) and less for Labor (10%). It created the minimum fuzzy total exergy of 24,251,604.43 & 25,381,554.37 (MJ) for coal SC by carbon trade and offset policies, respectively. Furthermore, exergy Set A (30-60-10) creates the worst sustainability performance in Australia under both carbon trade and offset policies since more exergy weight is assigned for Labor (60%) and less for Environment (10%).

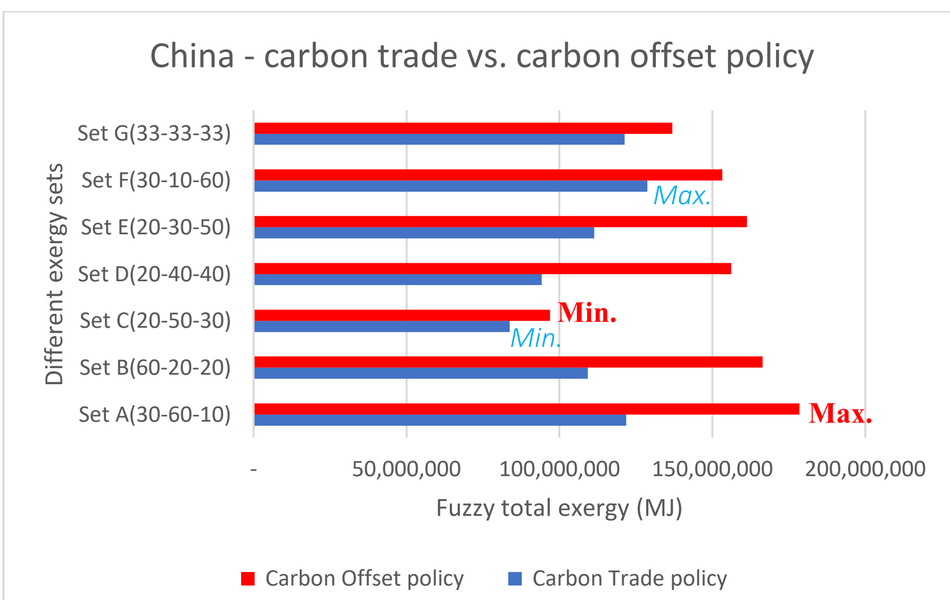


Fig. 8.2. Sustainability of coal SC in China under the carbon trade and offset policies

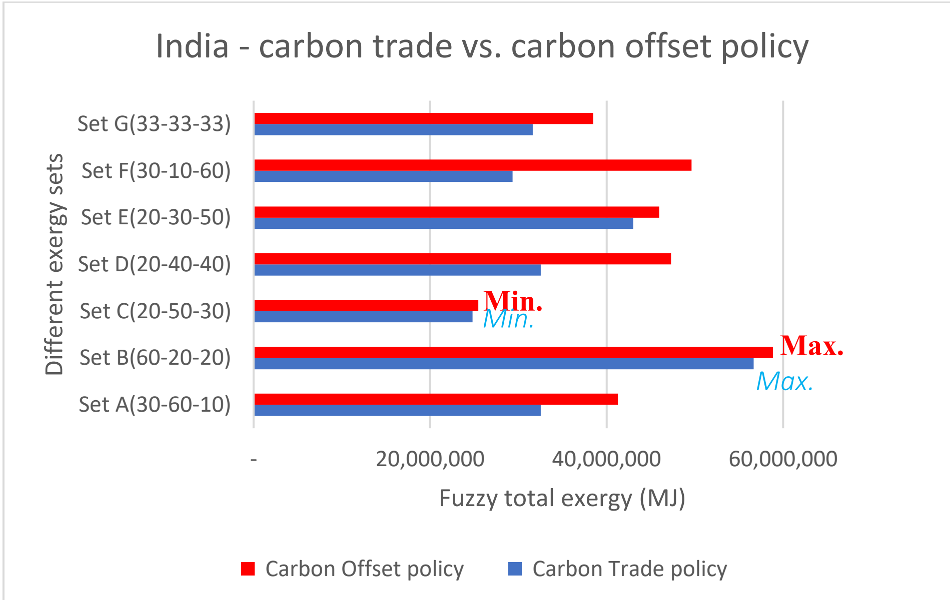


Fig. 8.3. Sustainability of coal SC in India under the carbon trade and offset policies

- **China** (Fig. 8.2): In the biggest coal consumer in the world (54%), the maximum sustainability performance of coal SC under both carbon trade and offset policies are with exergy Set C (20-50-30) when Labor has 50% weight, going along with Capital (20%) and Environment (30%), respectively. It created the minimum fuzzy total exergy of 83,731,242.82 & 96,953,009.68 (MJ) for coal SC by carbon trade and offset policies, respectively. Moreover, under carbon trade policy, this is exergy Set F (30-10-60) which creates the worst sustainability performance whereas only 10% is assigned to Labor element and 60% for Environment. Under carbon offset policy, exergy Set A (30-60-10) makes the worst sustainability performance in China when more exergy weight is supposed for Labor (60%) and only 10% for Environment.
- **India** (Fig. 8.3): In the second biggest coal consumer in the world (18%), like China, exergy Set C (20-50-30) with 50% Labor weight and 20% for Capital creates the best sustainability performance under both carbon trade and offset policies. It produced the minimum fuzzy total exergy of 24,826,136.13 & 25,466,158.69 (MJ) for coal SC in India by carbon trade and offset policies, respectively. Likewise, under both carbon trade and offset policies, this is exergy Set B (60-20-20) which creates the worst sustainability performance whereas 60% is assigned to Capital element.

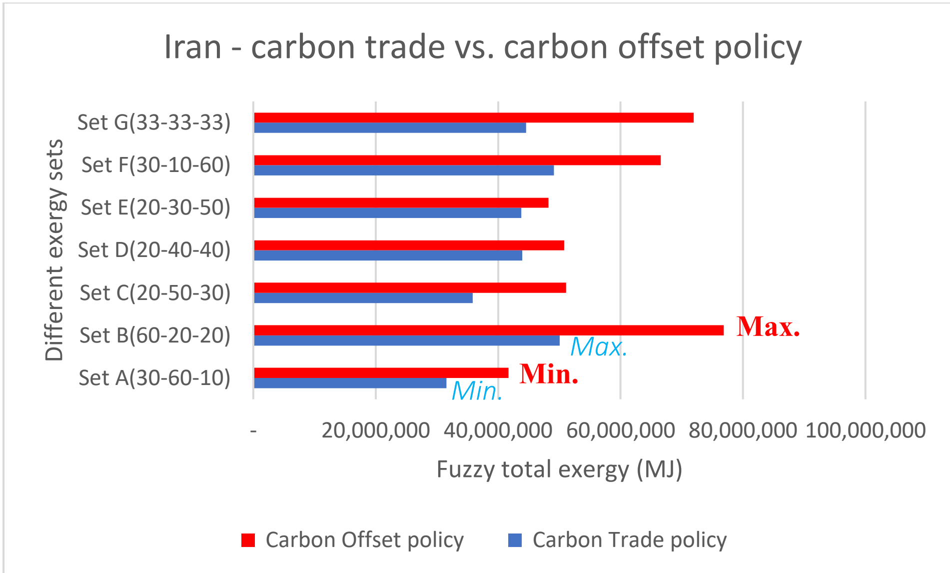


Fig. 8.4. Sustainability of coal SC in Iran under the trade and offset policies

➢ **Iran** (Fig. 8.4): In this developing country, the highest sustainability performance of coal SC is by exergy Set A (30-60-10), as Labor has 60% while Environment has only 10%. It made the minimum fuzzy total exergy of 31,537,292.44 & 41,699,351.48 (MJ) under both carbon trade and offset policies. Like India, the lowest sustainability performance is with exergy Set B (60-20-20), when 60% weight is allocated to Capital, which created the maximum fuzzy total exergy (MJ) under both carbon policies.

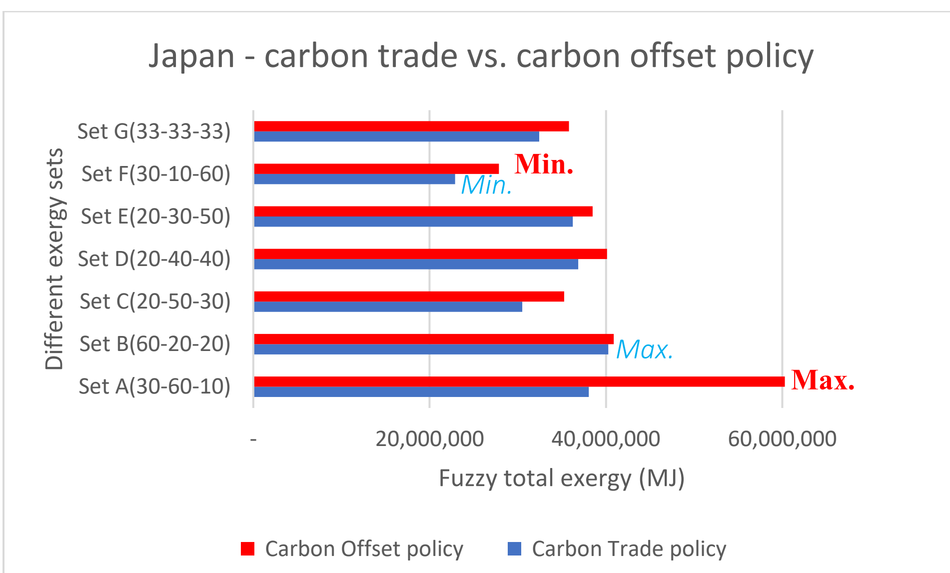


Fig. 8.5. Sustainability of coal SC in Japan under the carbon trade and offset policies

➢ **Japan** (Fig. 8.5): This developed country has the same sustainability conditions with Australia. The best sustainability performance under both carbon policies is with exergy Set F (30-10-60), while more exergy percentage is given to Environment (60%). It established the minimum amount of fuzzy total exergy with 22,873,547.02 & 27,876,026.26 (MJ) by carbon trade and offset policies, respectively. Moreover, the maximum fuzzy total exergy (the lowest sustainability in MJ) under carbon trade policy is with exergy Set B (60-20-20) when more weight is provided to the Capital (60%). Under carbon offset policy, this is exergy Set A (30-60-10) which creates the lowest sustainable condition when Labor and Environment elements have 60% and 10%, respectively.

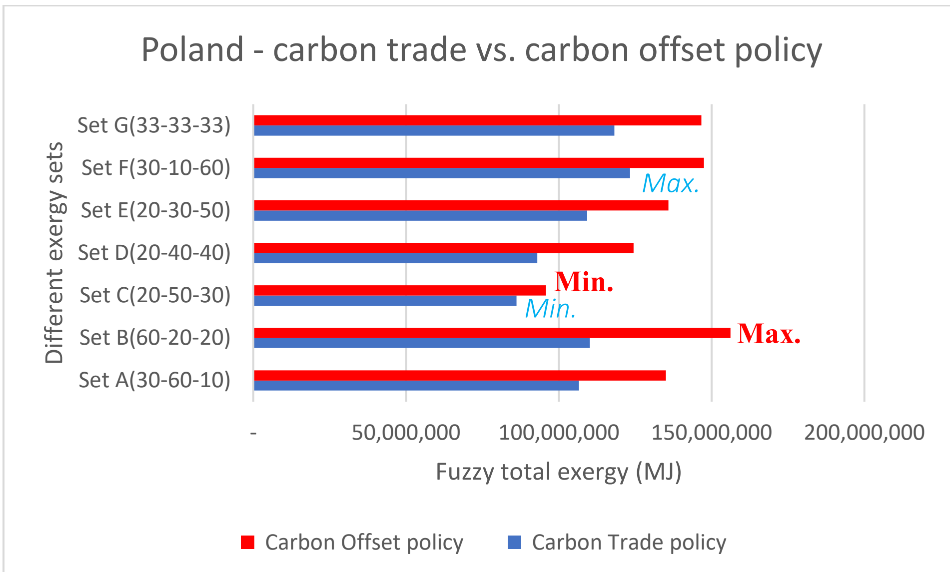


Fig. 8.6. Sustainability of coal SC in Poland under the carbon trade and offset policies

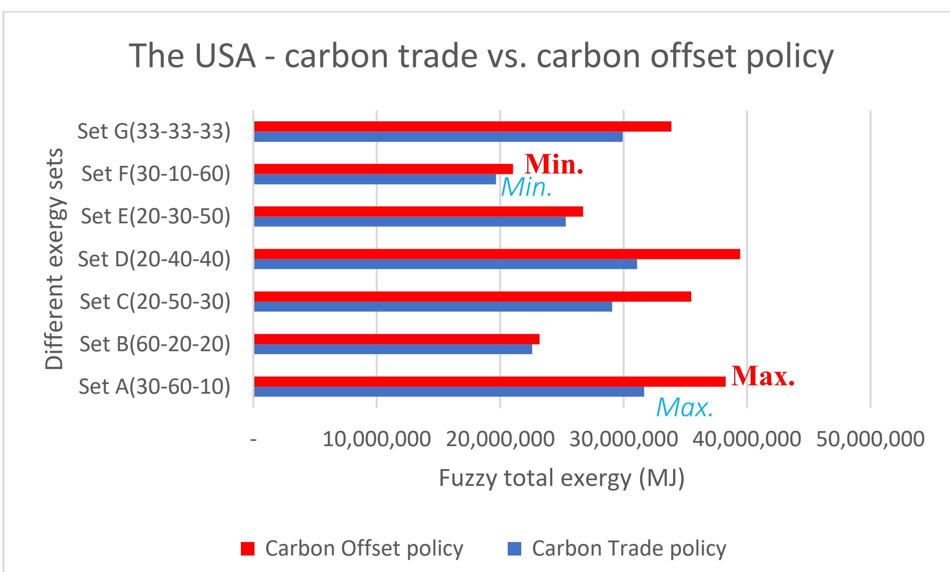


Fig. 8.7. Sustainability of coal SC in the USA under the carbon trade and offset policies

➢ **Poland** (Fig. 8.6): Poland ranks 9th in the world in coal consumption to generate 70% of electricity, by far the highest figure in Europe. Like India and China, the greatest sustainability performance of coal SC under both carbon trade and offset policies in Poland are with exergy Set C (20-50-30) when Labor has 50% weight, going along with Capital (20%) and Environment (30%), respectively. It created the lowest fuzzy total exergy of 86,131,627.76 & 95,760,363.89 (MJ) for coal SC by carbon trade and offset policies, respectively. Moreover, under carbon trade policy, this is exergy Set F (30-10-60) which generates the unhealthiest sustainability performance whereas only 10% is assigned to Labor element and 60% for Environment. Under carbon offset policy, exergy Set B (60-20-20) makes the lowest sustainability performance in Poland when more exergy weight is supposed for Capital (60%) and the same (20%) for Labor and Environment aspects.

➢ **The USA** (Fig. 8.7): This developed country is the third biggest coal consumers (6%) in the world. Like Australia and Japan, the highest sustainability performance of coal SC under both carbon trade and offset policies are with exergy Set F (30-10-60) since more exergy weight is assigned for Environment (60%) and less for Labor (10%). It created the lowest fuzzy total exergy of 19,675,609.14 & 21,032,559.94 (MJ) for coal SC by carbon trade and offset policies, respectively. Furthermore, exergy Set A (30-60-10) creates the worst sustainability performance in the USA under carbon trade policy since more exergy weight is assigned for Labor (60%) and less for Environment (10%). Under carbon offset, this is exergy Set D (20-40-40) which generates the lowest sustainability condition since only 20% is assigned to Capital and the same weights (40%) for both Labor and Environmental aspects.

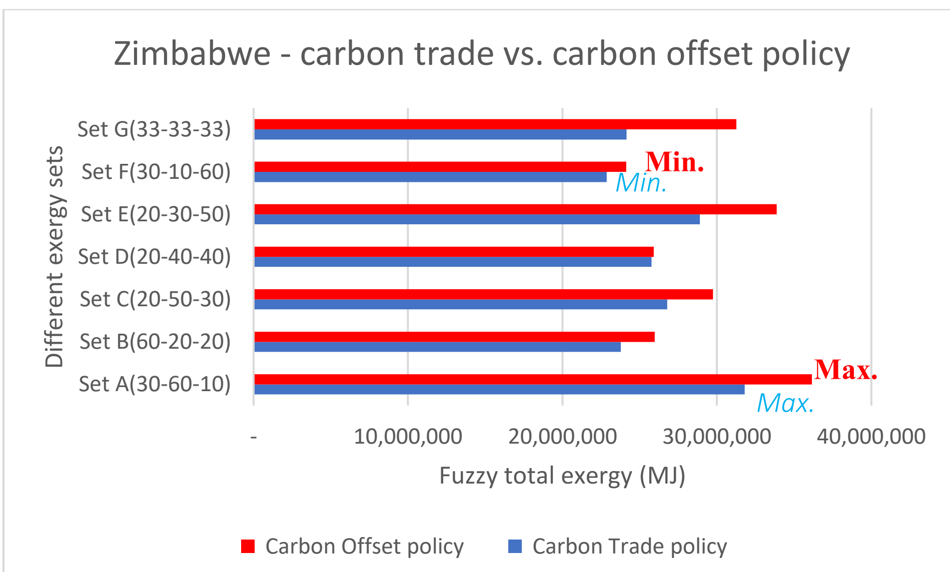


Fig. 8.8. Sustainability of coal SC in Zimbabwe under the carbon trade and offset policies

➢ **Zimbabwe** (Fig. 8.8): This African developing country has the same sustainability conditions with Australia, Japan, and the USA. The superior sustainability performance under both carbon policies is with exergy Set F (30-10-60), while more exergy percentage is given to Environment (60%) and only 10% for Labor. It established the least amount of fuzzy total exergy with 22,873,547.02 & 24,119,890.07 (MJ) by carbon trade and offset policies, respectively. Moreover, like Australia, the largest fuzzy total exergy (the lowest possible sustainability in MJ) under both carbon trade and offset policies in Zimbabwe is with exergy Set A (30-60-10) when more weight is provided to the Labor (60%) and only 10% for Environmental aspect.

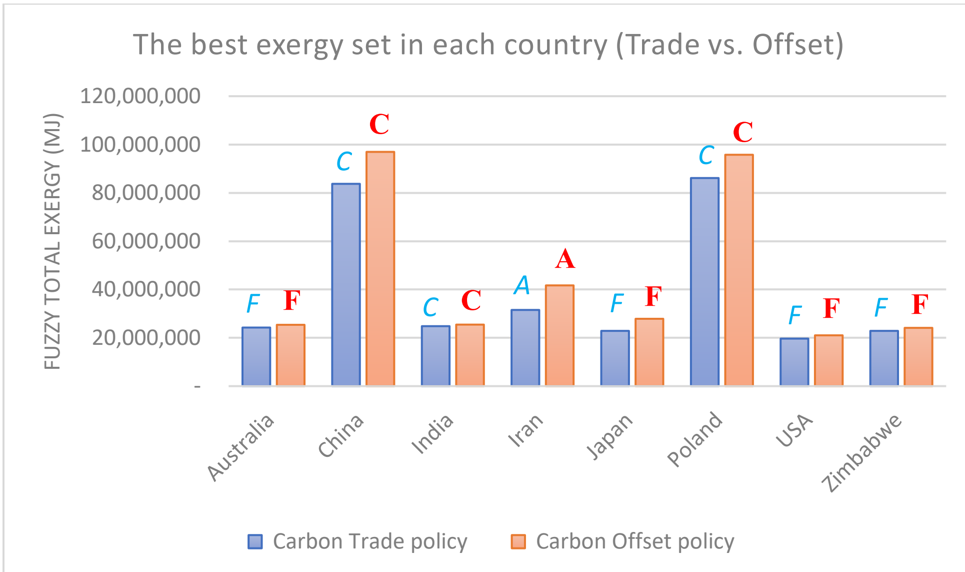


Fig. 8.9. The best exergy set for each country under the carbon trade and offset policies

- Respecting Fig. 8.9, the best exergy set (with the highest sustainability performance in MJ) in developing countries like Iran is exergy Set A (30-60-10) under both carbon trade and offset policies, while more exergy percentage is given to Labor (60%) and only 10% to Environment. Moreover, it is observed that Zimbabwe as a developing country in Africa has the same sustainability condition for coal SC with the developed countries like Australia, Japan, and the USA. The best exergy set for mentioned countries is Set F (30-10-60) when Environmental aspect has 60% weight and Labor only 10%. It creates the best sustainability performance (the lowest fuzzy total exergy in MJ) under both carbon trade and offset policies. In the two most populated countries like China and India, this is exergy Set C (20-50-30) which generates the best sustainable performance for coal SC since 50% weight is assigned to Labor. Coal SC in Poland (in the Europe) has the same condition with China and India.
- Among all presented developed and developing countries, the coal SC in the USA has the lowest total exergy (the most sustainable conditions) with 22,604,564.59 & 23,177,067.92 (MJ) under carbon trade and offset policies, respectively (see Fig. 8.9). Zimbabwe, Japan, Australia, India, China, and Poland are followed the USA.

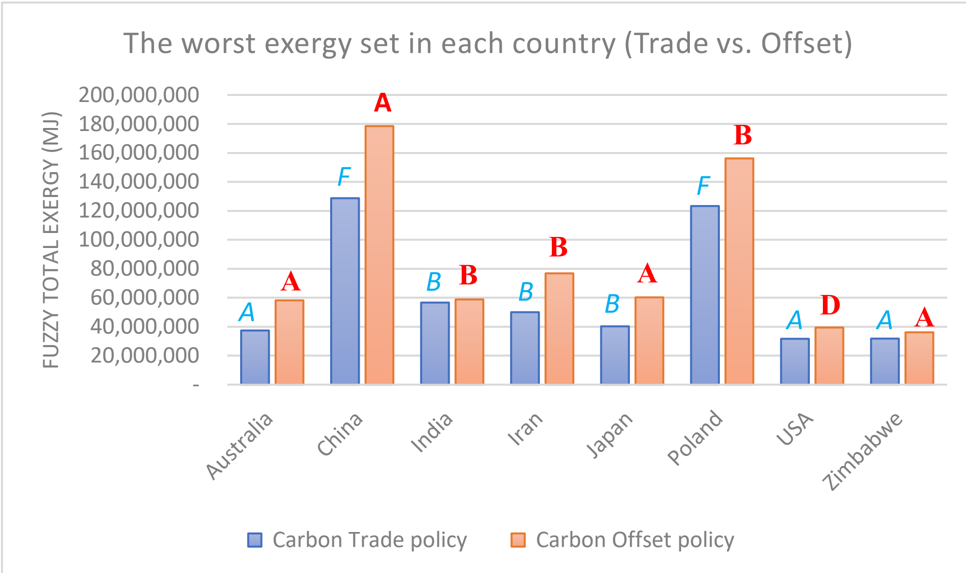


Fig. 8.10. The worst exergy set for each country under the carbon trade and offset policies

- Respecting Fig. 8.10, under carbon trade policy the worst exergy set (the lowest sustainability with the highest fuzzy total exergy in MJ) in Australia, the USA and Zimbabwe is exergy Set A (30-60-10) with 60% Labor weight and only 10% for Environmental aspect. In China and Poland, exergy Set F (30-10-60) with 60% Environmental weight and only 10% for Labor aspect is the worst exergy set under the carbon trade policy. Moreover, in India and Iran exergy Set B (60-20-20) creates the lowest sustainable performance when 60% weight is assigned to Capital and the same weights (20%) for Labor and Environmental aspects.
- Concerning Fig. 8.10, under carbon offset policy the worst exergy set (the minimal sustainability with the greatest fuzzy total exergy in MJ) in Australia, China, Japan and Zimbabwe is exergy Set A (30-60-10) with 60% Labor weight and only 10% for Environmental aspect. In India, Iran and Poland, exergy Set B (60-20-20) with 60% Capital weight and the same weights (20%) for Labor and Environmental aspects is the worst exergy set under the carbon offset policy. Moreover, in the USA exergy Set D (20-40-40) creates the lowest sustainable performance when only 20% weight is assigned to Capital and the same weights (40%) for Labor and Environmental aspects.
- Moreover, coal SC in China has the highest fuzzy total exergy (the lowest sustainability conditions) among all presented developed and developing countries with 121,884,457.74 & 178,509,576.98 (MJ) under both carbon trade and offset policies, respectively (see Fig. 8.10).

8.6.2 Analysis of each exergy set-carbon trade and offset policies

Considering Table 8.1 for each exergy set, we have:

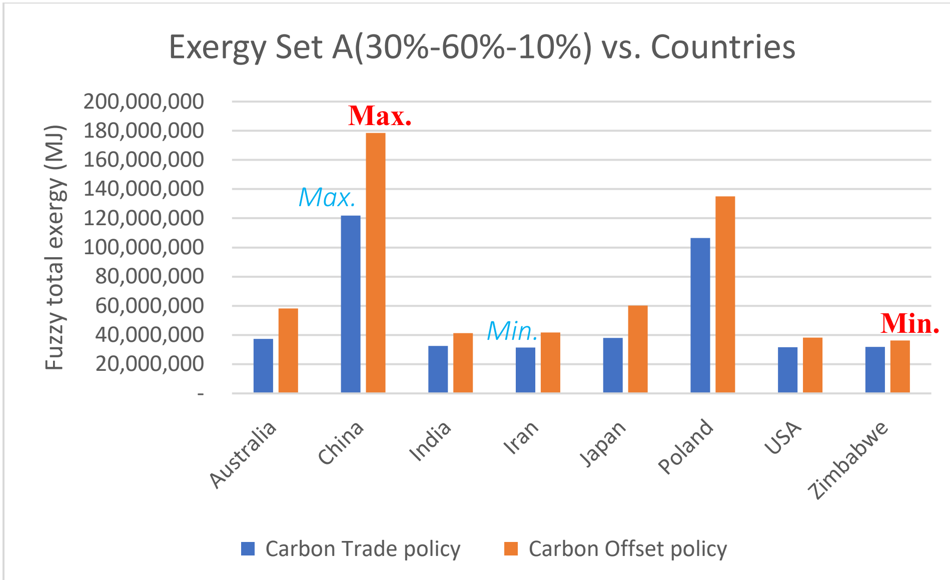


Fig. 8.11. The exergy Set A in developed and developing countries under the carbon trade and offset policies.

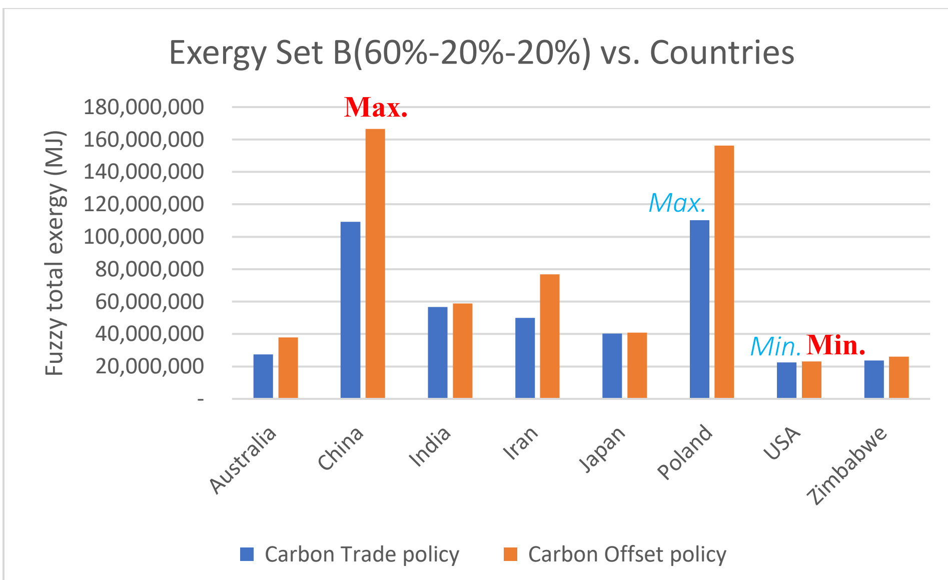


Fig. 8.12. The exergy Set B in developed and developing countries under the carbon trade and offset policies.

- **Exergy Set A (30%-60%-10%):** Considering this exergy set which has 60% weight for Labor (60%) and only 10% to Environment, creates the most sustainable performance (the lowest fuzzy total exergy in MJ) among all the countries in Iran (31,537,292.44) under carbon trade and in Zimbabwe (36,156,127.01) under carbon offset policy. At the same time, exergy set A creates the worst sustainability performance with the highest fuzzy total exergy (MJ) in China under both carbon policies (see Fig. 8.11).

➢ **Exergy Set B (60%-20%-20%):** Regarding this exergy set which has more emphasis on Capital (60%), coal SC in the USA has the lowest sustainability performance (the highest fuzzy total exergy in MJ) under both carbon policies. At the same time, exergy set B works unhealthy in terms of MJ in Poland (110,155,055.08) and China (166,472,938.65) under carbon trade and offset policies, respectively (see Fig. 8.12).

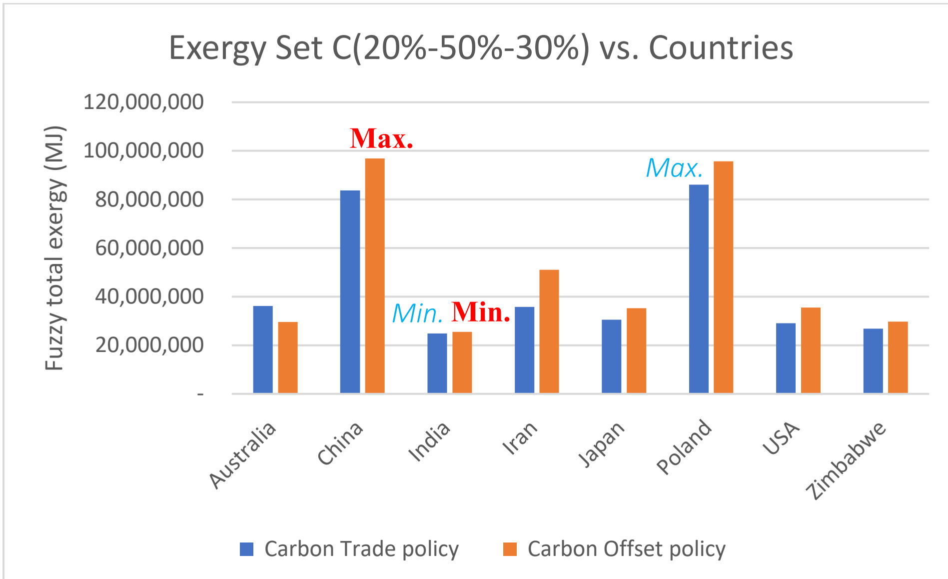


Fig. 8.13. The exergy Set C in developed and developing countries under the carbon trade and offset policies.

➢ **Exergy Set C (20%-50%-30%):** In this exergy set is assigned more weight on Labor (50%) which creates the best sustainability conditions among all the countries for coal SC in India under both carbon policies. Simultaneously, it creates the lowest sustainability conditions (in MJ) in Poland (86,131,627.76) and China (96,953,009.68) under carbon trade and offset policies, respectively (see Fig. 8.13).

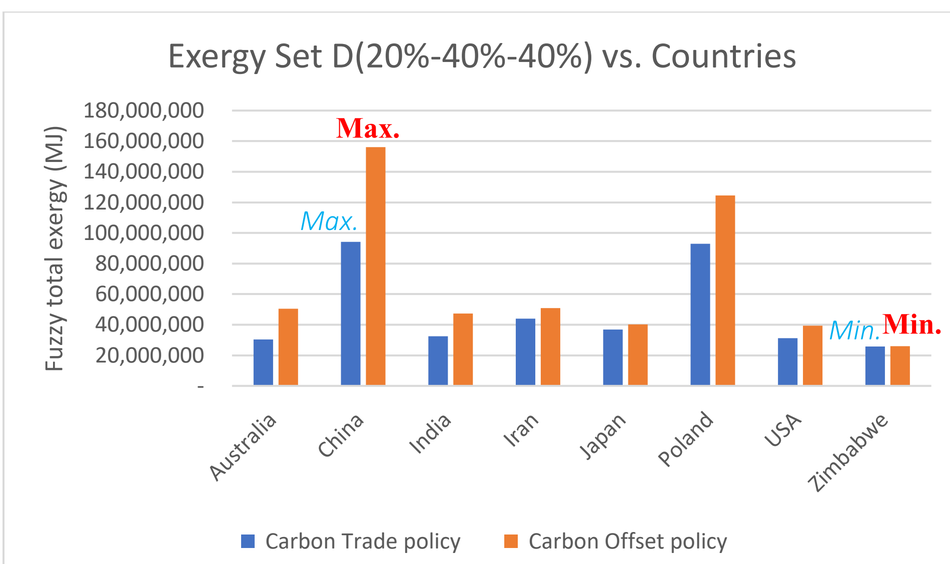


Fig. 8.14. The exergy Set D in developed and developing countries under the carbon trade and offset policies.

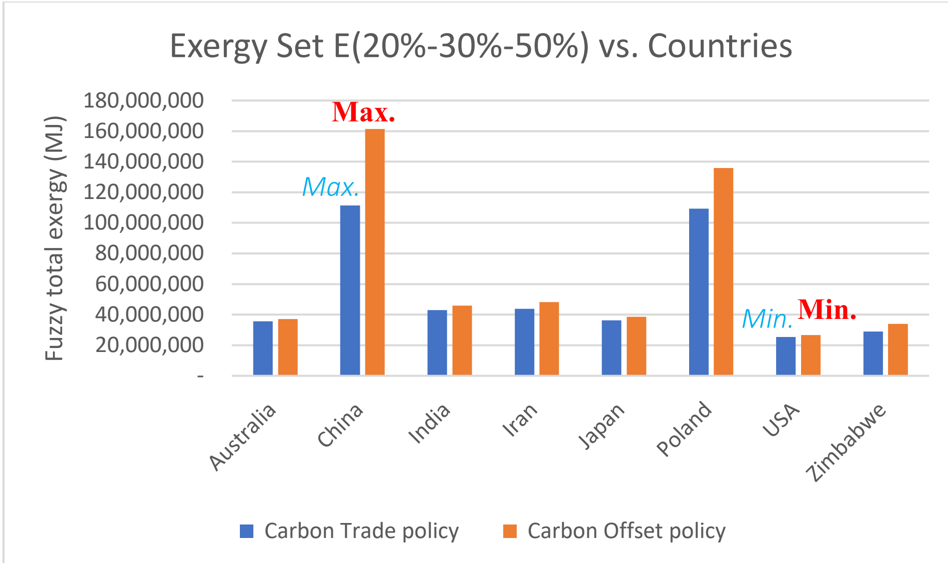


Fig. 8.15. The exergy Set E in developed and developing countries under the carbon trade and offset policies.

- **Exergy Set D (20%-40%-40%):** When less emphasis is put on Capital (20%) and the same weights (40%) for Labor and Environmental aspects, exergy set D creates the worst sustainability conditions among all the countries in China under both carbon trade and offset policies. All at once, it operates well in terms of sustainability (the lowest fuzzy total exergy) in Zimbabwe under both carbon policies (see Fig. 8.14).
- **Exergy Set E (20%-30%-50%):** In this set, 50% weight is assigned to Environmental aspect and only 20% for Capital. It creates the highest fuzzy total exergy (the lowest sustainability) in China and the lowest (the highest sustainability) in the USA under both carbon trade and offset policies (see Fig. 8.15).

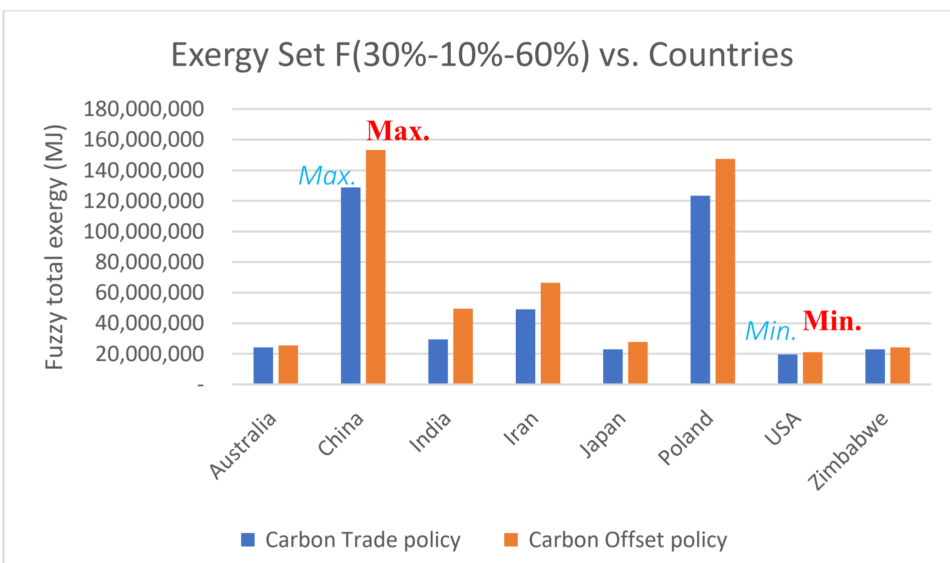


Fig. 8.16. The exergy Set F in developed and developing countries under the carbon trade and offset policies.

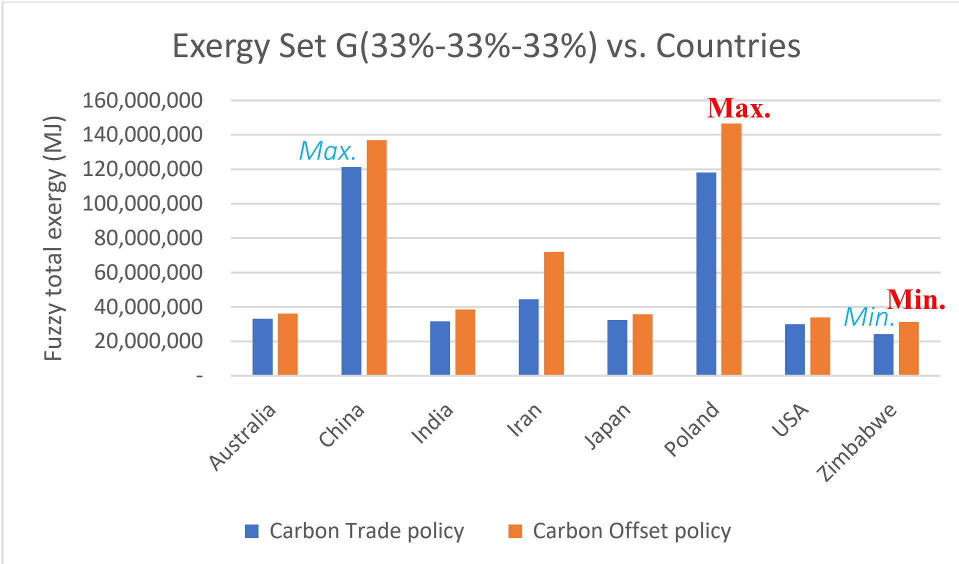


Fig. 8.17. The exergy Set G in developed and developing countries under the carbon trade and offset policies.

- **Exergy Set F (30%-10%-60%):** With 60% weight for Environmental aspect and only 10% for Labor, Set F creates the maximum fuzzy total exergy (the minimal sustainability) in China (128,734,240.79 & 153,294,716.80 MJ) and the minimal (the maximum sustainability) in coal SC in the USA under both carbon trade and offset policies (see Fig. 8.16).
- **Exergy Set G (33%-33%-33%):** In this set, the same weights (33%) are given to all sustainability aspects. It creates the lowest fuzzy total exergy (the highest the sustainability) in Zimbabwe under both carbon trade and offset policies. Moreover, the weakest sustainability condition in terms of MJ is belong to China (121,351,102.11) and Poland (146,622,025.05) under carbon trade and offset policies, respectively (see Fig. 8.17).
- Moreover, all exergy Sets (A-E) generated the maximum fuzzy total exergy (the lowest sustainability) for coal SC in China and Poland among all presented countries under both carbon trade and offset policies (see Table 8.1).

In this chapter, carbon offset policy is applied to the EPQ model in Chapter 6 to make a comparison between the carbon trade and offset policies in terms of Joules in a coal SC among some developed and developing countries such as India, China, Iran, Australia, Japan, Poland, the USA, and Zimbabwe. All sensitivity results are presented in Table 8.1 for coal SC in all countries. Moreover, analysis of each country (subsection 8.6.1) and analysis of each exergy set (subsection 8.6.2) for both carbon tax and cap policies are presented in this chapter. In the next chapter, a comprehensive conclusion for all four carbon policies and related models will be presented as well as the research limitations and future research.

CHAPTER 9. CONCLUSIONS AND FUTURE WORK

In this manuscript-based thesis, a comprehensive literature review about sustainability management in SC and demand forecast in energy SC was done in Chapters 3 and 4, respectively. Moreover, research works related to exergy analysis and carbon reduction policies in the past two decades were reviewed in Chapters 5 (subsection 5.2) and 6 (subsection 6.2). According to the literature review, there is a lack of studies that assess a coal SC under any carbon reduction policies such as carbon cap, tax, trade and offset with ambiguous parameters for example, carbon price and customer demand. Likewise, little research has been done to assess a SC in terms of Joules (in place of traditional monetary measures of performance) and simultaneously evaluates all sustainability characteristics (economic, labour, and environmental). Similarly, to the best of the authors' knowledge, no exergy analysis method like the extended exergy accounting (EEA) in the literature considers carbon reduction policies in SC. Therefore, this dissertation developed the work of Jawad et al. (2016) and Naderi et al. (2021a) to a multi-product multi-limitation inventory (EOQ/EPQ) model with backorder for a coal SC in Iran under an uncertain environment. By applying the EEA technique and Mega-Joules (*MJ*) as a universal unit of measure, the total exergy of the coal SC can be calculated. Moreover, the sustainability performance of coal SC in terms of Joules (considering economic, labour, and environmental aspects) in developed and developing countries under four well-known carbon reduction strategies such as carbon tax (Chapter 5), carbon trade (Chapter 6), carbon cap (Chapter 7) and carbon offset (Chapter 8) are evaluated.

In Chapter 5, a carbon tax policy was applied to a coal SC in Iran, Afghanistan, Turkey, Canada and Germany under EOQ inventory model and then the mathematical model was converted to an exergy model (in terms of Joules) by the EEA method. The model was solved by some traditional and modern metaheuristic algorithms (WOA, GA, ACO, and SA). The results of metaheuristic algorithms were validated by exact method (GAMS software) in small size test problems. Finally, a sensitivity analysis for different weights of exergy aspects (Capital, Labor and Environment) for all countries was done to find out which exergy weight is creating the most sustainable performance for coal SC in each country. In the same way, in Chapter 6, carbon trade policy was applied to a coal SC in India, China, Iran, Australia, Japan, Poland, the USA, and Zimbabwe. The same solution process was done for this chapter while three recent metaheuristic algorithms: ALO, LOA, and WOA were employed to solve the model. Chapter 7 developed the model in Chapter 5 by employing carbon cap policy. Similarly, Chapter 8 developed the model in Chapter 6 by employing carbon offset policy. Moreover, a comparison between the carbon cap and tax policies in Chapter 7 and between carbon trade and offset policies in Chapter 8 was made.

9.1 Research contributions

In earlier studies, as we saw in Chapters 1 and 2, there were some research gaps that this study tried to fill them. Therefore, this PhD thesis contributes to the literature by assess a coal SC include one vendor and multi-buyer with multi-product and multi-limitation inventory models (EOQ/EPQ) with backorder under four different carbon reduction policies such as carbon tax (Chapter 5), carbon cap (Chapter 7), carbon trade (Chapter 6) and carbon offset (Chapter 8) within an uncertain environment, for example, carbon price or customer demand. Moreover, this study assessed a SC in terms of Joules instead of dollars (as a traditional performance measures) and simultaneously evaluate all sustainability aspects, such as economic, labour, and environmental. Furthermore, to the best author's knowledge, this is the first study that employ the EEA method to assess the sustainability of a coal SC under four carbon emission policies. Additionally, this study compared the sustainability of coal SCs between developed and developing countries under carbon tax and cap policies (in Chapters 5 and 7 among Iran, Afghanistan, Turkey, Germany, and Canada) and under carbon trade and offset policies (in Chapters 6 and 8 among Iran, Australia, China, India, Japan, Poland, the USA, and Zimbabwe) with the EEA method. Besides, this thesis obtained the best percentage of exergy components (social, economic, environmental aspects) in the EEA method for a coal SC in both developed and developing countries (please see Tables 7.1 and 8.1) that created the highest sustainability performance and the lowest total exergy in MJ. Likewise, this study compared the sustainability of coal SC in both developed and developing countries and obtained which country has the best sustainability performance (the lowest total exergy) in terms of Joules (please see Figs. 7.6 and 8.9).

In this dissertation, four research questions (in Chapter 1) were presented. We summarize the answers to each in this section and highlight the research contributions.

Q1. Does incorporating a carbon reduction strategy with the EEA method in coal SC trigger financial benefits and sustainability advantages?

In Chapters 5-8, four non-exergy mathematical models of the coal SC under carbon cap, tax, trade, and offset policies were developed. Then the models were converted to fuzzy models, and finally, a new SC assessment method called the EEA (in terms of Joules) was employed for all models. This method contains energy and material's main aggregate exergy subject and costs corresponding to economic externalities (labor and capital) and ecological externality (environmental remediation). Therefore, employing this method could benefit both the economy and the environment. By employing well-known and recent metaheuristic algorithms (GA, ACO, SA, ALO, LOA, and WOA) all models were solved, and their results were verified by the exact method (GAMS software) in small-size test problems (four products).

Q2. The coal SC in developing countries is supposed to have the lowest cost overall; however, in terms of sustainability (social, economic, and environmental aspects) and considering Joules rather than monetary objectives, does this assumption remain accurate?

Regarding the sensitivity analysis in Chapters 5-8, the sustainability of coal SC under carbon cap and tax policies were compared in five developed and developing countries such as Afghanistan, Iran, Turkey, Germany, and Canada (see Table 7.1). Moreover, under the carbon trade and offset policies, eight developed and developing countries, such as Iran, India, China, Australia, Japan, Poland, the USA, and Zimbabwe were assessed (see Table 8.1). They are the world's most significant coal-consuming countries (Statista, 2020).

- Under carbon cap and tax policies:
    - It is observed that coal SCs in developing countries such as Iran and Turkey have lower sustainability performance in MJ than the developed countries such as Germany and Canada under carbon cap and tax policies.
- Under carbon trade and offset policies:

- It is observed that coal SCs in the developing countries such as India and China have lower sustainability performance in MJ than the developed countries such as the USA, Japan and Australia under carbon trade and offset policies.

The reason behind this issue is that traditional assessment methods consider economic measures only. In contrast, the method of EEA considers all three aspects of sustainability (Labour, Money, and Ecological remediation) in goods or services. It determines their corresponding exergy (in terms of Joules rather than Dollar or Euro) by some elements significantly affected by population, normal workload, labor statistics, and local and international wages in each country. Therefore, the EEA method results show the total number of Joules that coal SC utilized in Labour, Money, and Ecological aspects.

Q3. Which country has the most sustainable coal SC in terms of Joules?

- Based on Table 7.1 and under carbon cap and tax policies, among all five presented countries (developed and developing), the coal SC in Afghanistan has the lowest total exergy (the best sustainable conditions) with 141,316.53 & 1,504,757.85 (MJ) under carbon cap and tax policies, respectively (see Fig. 7.6). Germany, Canada, Iran, and Turkey followed Afghanistan. It is observed that coal mining and related enterprises in the developed countries such as Germany and Canada have economic and environmental advantages compared to developing countries such as Iran and Turkey in terms of MJ.
- Additionally, based on Table 8.1 and under carbon trade and offset policies, the minimal total exergy (the best sustainable performance) of a coal SC among all eight countries belongs to the USA with 22,604,564.59 & 23,177,067.92 (MJ) under carbon trade and offset policies, respectively (see Fig. 8.9). Zimbabwe, Japan, Australia, India, China, and Poland followed the USA. It means coal mining and related businesses in the USA have monetary and ecological benefits contrasted to developing countries (like China and India or Iran and Zimbabwe) in terms of MJ.

Q4. What is the best percentage of exergy components (social, economic, environmental characteristics) to achieve the greatest saving wherever coal SCs are working?

- Under carbon cap and tax policies:
  - Respecting Fig. 7.6 and Table 7.1, the best exergy set in developing countries like Afghanistan, Iran and Turkey is exergy Set A (30-60-10), while more exergy percentage is given to Labor (60%) and only 10% to Environmental aspect. It creates the best sustainability conditions with the lowest fuzzy total exergy in MJ. Moreover, in developed countries like Canada and Germany, the best exergy set is Set D (30-20-50) with 50% Environmental weight which creates the best sustainability performance under both carbon cap and tax policies.
- Under carbon trade and offset policies:
  - Respecting Fig. 8.9 and Table 8.1, the best exergy set (with the highest sustainability performance in MJ) in developing countries like Iran is exergy Set A (30-60-10) under both carbon trade and offset policies, while more exergy percentage is given to Labor (60%) and only 10% to Environment. Moreover, it is observed that Zimbabwe as a developing country in Africa has the same sustainability condition for coal SC with the developed countries like Australia, Japan, and the USA. The best exergy set for mentioned countries is Set F (30-10-60) when Environmental aspect has 60% weight and Labor only 10%. It creates the best sustainability

performance (the lowest fuzzy total exergy in MJ) under both carbon trade and offset policies. In the two most populated countries like China and India, this is exergy Set C (20-50-30) which generates the best sustainable performance for coal SC since 50% weight is assigned to Labor. Moreover, Coal SC in Poland (in the Europe) has the same condition with China and India.

9.2 Management implications and future research

There are some observations based on the results for improving the sustainability of coal SC in each country are presented in what follows.

The exergy equations in Chapters 5-6 (for instance, Eqs. 5.20-5.34) showed that the all exergy parameters such as capital, labor and environmental aspects ($ee_{Cap,i}, ee_{L,i}, ee_{Env,i}$) had direct relation to the cost elements of inventory models such as setup/ordering (K), purchasing (C), and holding(h). Consequently, these inventory costs affect the total exergy of the coal SC in a significant way. It is therefore critical to decrease the cost elements of a coal SC's inventory model to improve sustainability. For example, by using stock classification and shorter order cycles, reducing the lead time of suppliers, eliminating obsolete inventory, implementing a Just-in-Time inventory system, and monitoring key performance indicators.

Unlike conventional financial and commercial models, the results of our study found that a way to improve the sustainability performance of coal SC is tuning of the weights that are assigned to the exergy of capital, Labor and Environmental aspects in each country (see Tables 7.1 and 8.1). It means that no fixed amount of exergy components (Capital, Labor and Environment) can deliver the highest sustainability in all countries. For example, according to the results in Table 8.1, exergy Set F (30-10-60) with 60% weight allocated to the environment and only 10% to labor generates the best sustainability for coal SC in the USA (19,675,609.14 & 21,032,559.94 MJ) under both carbon trade and offset policies. Simultaneously, this exergy Set generates the worst sustainability for China (128,734,240.79 & 153,294,716.80 MJ). Hence, finding the best amount of exergy elements (capital, labor and environment) for each country and try to tune them is important.

Another point is that, considering Appendix 3-Table A.9.1 (which is made by integrating Tables 5.5-6.5) and Appendix 3-Fig. A.9.1, one can conclude that the exergy parameters of Capital ($ee_{Cap} = 1.1$ MJ/Euro) and Labor ($ee_L = 0.41$ MJ/WH) in Afghanistan are less than all presented countries. This would be one of the reasons why coal SC in Afghanistan has the most sustainable performance in terms of Joules under carbon cap and tax policies, whereas Iran ($ee_{Cap} = 5.68$ MJ/Euro) and Turkey ($ee_{Cap} = 20.51$ MJ/Euro) have the worst sustainable condition. Similarly, for example, under carbon trade and offset policies, the exergy parameter of Capital ($ee_{Cap} = 2.85$ MJ/Euro) in the USA is less than Japan, Australia, India, China, Poland, and Zimbabwe. However, China ($ee_{Cap} = 14.01$ MJ/Euro) and Poland ($ee_{Cap} = 14.02$ MJ/Euro) are the worst sustainable conditions under carbon trade and offset policies. Therefore, a way to increase sustainability in each country is to find ways to decrease exergy parameters (ee_{Cap}, ee_L).

If we look at exergy formulas of Capital ($ee_{Cap} = \alpha_x . \beta_x \left(\frac{Ex_{in}}{M_2}\right)$) and Labor ($ee_L = \frac{\alpha_x . Ex_{in}}{(NWH)_{total}}$) in Chapters 5-6, both exergy parameters (ee_{Cap}, ee_L) are dependent on two econometric coefficients (α_x, β_x) as well as (Ex_{in}). Chapters 5-6 explain that these values are influenced by the type of societal organization, the historical period, the technological level, the pro-capital resource consumption, and the geographical location of the country (Sciubba, 2011). Therefore, to decrease these parameters and consequently improving sustainability of coal SC, all shareholders, governments, individuals, societies, business organisations, scientists, etc., need to contribute significantly to adjusting the parameters, if possible. An example is controlling the import and export of goods from and to the country or extracting ores and minerals. Promoting locally made goods can be a way for individuals, societies, and business organizations to support this cause. As a result, there would be more jobs available in the country, and increasing the labor force rate (Jawad et al., 2018). Additionally, effective productivity growth (output per hour worked) can boost a country's income and GDP per capita. For more information, readers are encouraged to consult Sciubba (2011).

In addition, decision-makers should find ways to improve the sustainability of their coal SC by reducing waste, labor, material, and pollution, which will reduce the damaging effects of coal SC. When calculating energy costs, managers of SC would have more flexibility since they could use available resources rather than just capital to calculate the quantity. Furthermore, this research will also guide managers of international coal mining companies who wish to decide which country has more sustainable conditions for their business and investments.

Additionally, the EEA method in this thesis is subject to some restrictions, involving the following:

- When EEA is used to a coal SC, the precision of the results is dependent upon the assumptions made.
- It is possible that the EEA method in coal SCs may have restrictions when more than one country is included in the SC processes (international companies).
- Insufficient data regarding a country's total exergy input, the quantity of exergy represented in the workforce, the exergy of raw materials and energy consumed to supply a coal.

Moreover, the following avenues for future research are suggested for consideration:

a) A coal production system.
b) A model with multiple objectives (integrating inventory measures).
c) An international coal SC model that works in more than one country at the same time.
d) Comparing a global coal SC with a national one.
e) The strategy of increasing carbon price with increasing the amount of carbon (price dependent on amount) by each country.
f) A sensitivity analysis for different carbon cap limitation by each country under carbon cap policy.
g) The SC of coal power plants.
h) Quantity discounts in cost per unit of products can be allowed.
i) Interval type 2 fuzzy parameters can be considered.
j) Multi-echelon SCs, for example, single-buyer multi-supplier and multi-buyer multi-supplier SCs, can be investigated.
k) Lead times can be included.

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APPENDIX

Appendix 1. The results of carbon cap policy for the model (in chapter 7)

A.7.5.1.1. Part 1: *Find out the "near-optimum" solutions by metaheuristic algorithms.*

In this phase, each individual solution algorithms are performed ten times for each fuzzy exergy numerical example in Iran. Correspondingly, the lowest fuzzy total exergy and the CPU times (seconds) under emission cap policy (Eq. 7.17) are detailed in Tables A.7.1 and A.7.2.

The most exemplary metaheuristic algorithm is observed by revealing the proportion distinction between their outcomes. In this sustainable model under emission cap policy, we optimize three objectives simultaneously: the total inventory cost, the total cost associated with the additional required budget of all buyers, and the penalty cost of coal waste disposal to the environment. We converted all model economic parameters (Euro) to equivalent exergy values (MJ) using the EEA method. Therefore, considering this model's three fuzzy exergy objective functions, GA is the best individual algorithm with the lowest fuzzy total exergy for numerical examples for 4-, 8-, 32- and 64-item (734,740.68 to 12,173,554.77 MJ). For 16-, 128-, 256- and 512-item test problems, this is WOA that has better performance (from 2,949,449.28 to 98,415,908.27 MJ) in terms of fuzzy total exergy (see Table A.7.1). Moreover, for the large size numerical test 1024-item, ACO has the lowest fuzzy total exergy (190,647,152.57 MJ).

A comparison of algorithms in terms of the fuzzy total exergy under emission cap for large size numerical examples (256-, 521- & 1024-items) is presented in Fig. A.7.1 It should be mentioned that the enhancement percentages between results of the algorithms in all test problems are on average 0.25%. It means the results of the algorithms are remarkably close (see Fig. A.7.2).

Moreover, considering the CPU time (sec.), SA has the lower computational time than WOA in all examples (Table A.7.2 and Fig. A.7.3). Additionally, improvement percentage of computational time of SA against WOA is on average 1956% (see Fig. A.7.4).

Table A.7.1: The fuzzy total exergy cost found by the algorithms (Eq. 7.17) in Iran-Carbon cap

No. of items	Fuzzy total exergy (MJ)				The best algorithm	Difference	Improvement %
	WOA	**GA**	**ACO**	**SA**			
4	735,481.42	734,740.68	739,490.90	802,698.43	GA-WOA-ACO-SA	740.74	0.10
8	1,472,746.99	1,469,178.46	1,478,807.46	1,560,189.65	GA-WOA-ACO-SA	3,568.53	0.24
16	2,949,449.28	2,967,396.49	2,961,160.37	3,285,578.02	WOA-ACO-GA-SA	11,711.09	0.40
32	6,061,754.97	6,047,430.96	6,228,661.83	6,551,751.76	GA-WOA-ACO-SA	14,324.01	0.24
64	12,251,820.41	12,173,554.77	12,477,013.36	13,062,097.03	GA-WOA-ACO-SA	78,265.64	0.64
128	24,424,801.87	24,526,297.92	24,544,711.78	26,387,790.72	WOA-GA-ACO-SA	1,496.05	0.01
256	48,967,341.60	49,287,027.51	49,347,197.38	52,900,955.14	WOA-GA-ACO-SA	119,685.91	0.24
512	98,415,908.27	99,459,675.15	98,917,404.26	105,911,477.76	WOA-GA-ACO-SA	43,766.88	0.04
1024	191,349,070.21	196,899,307.13	190,647,152.57	211,717,247.50	ACO-WOA-GA-SA	701,917.64	0.37
Exact method's result (4 items) = 715,249.78 (MJ); Difference with GA=19,490.90; % Error=2.72							

Table A.7.2: The CPU times of solving test problems by the algorithms (Eq. 7.17) in Iran-Carbon cap

No. of items	CPU time (second)				The best algorithm	Difference	Improvement %
	WOA	**GA**	**ACO**	**SA**			
4	0.180	0.246	0.397	0.025	SA-WOA-GA-ACO	0.155	620.00
8	0.232	0.260	0.564	0.026	SA-WOA-GA-ACO	0.206	792.31
16	0.303	0.363	0.908	0.027	SA-WOA-GA-ACO	0.276	1022.22
32	0.456	0.559	1.763	0.029	SA-WOA-GA-ACO	0.427	1472.41
64	0.640	0.777	3.531	0.033	SA-WOA-GA-ACO	0.607	1839.39
128	1.196	1.337	6.246	0.047	SA-WOA-GA-ACO	1.149	2444.68
256	2.345	2.633	12.833	0.077	SA-WOA-GA-ACO	2.268	2945.45
512	4.245	4.914	24.854	0.125	SA-WOA-GA-ACO	4.120	3296.00
1024	7.991	8.872	48.196	0.244	SA-WOA-GA-ACO	7.747	3175.00
Exact method's result (4 items) = 4.29 Sec.; Difference with GA=4.04 Sec.; % Error=1643.90							

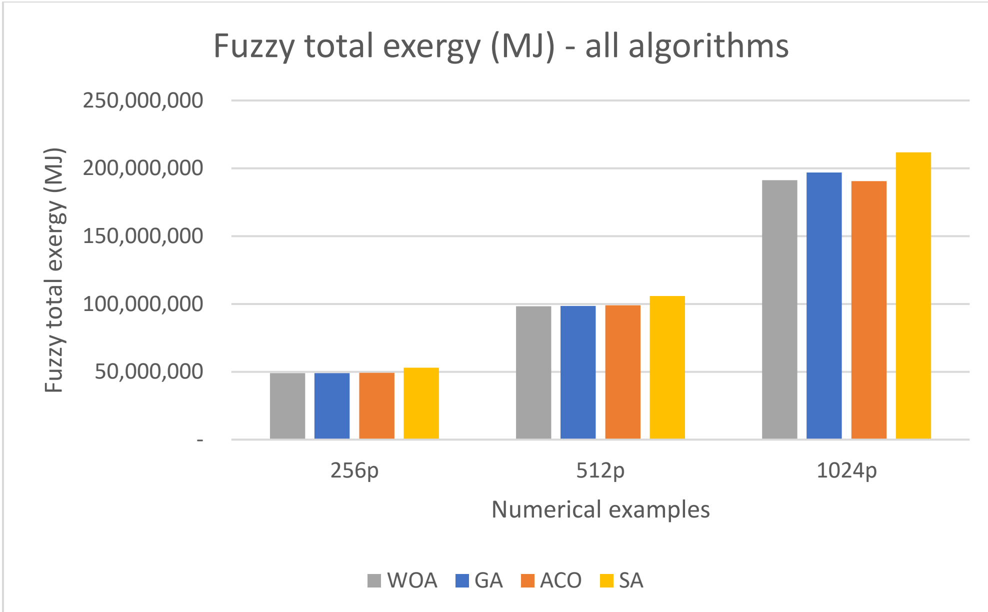

Fig.A.7.1. The fuzzy total exergy comparisons of all algorithms - carbon cap (Phase 2)

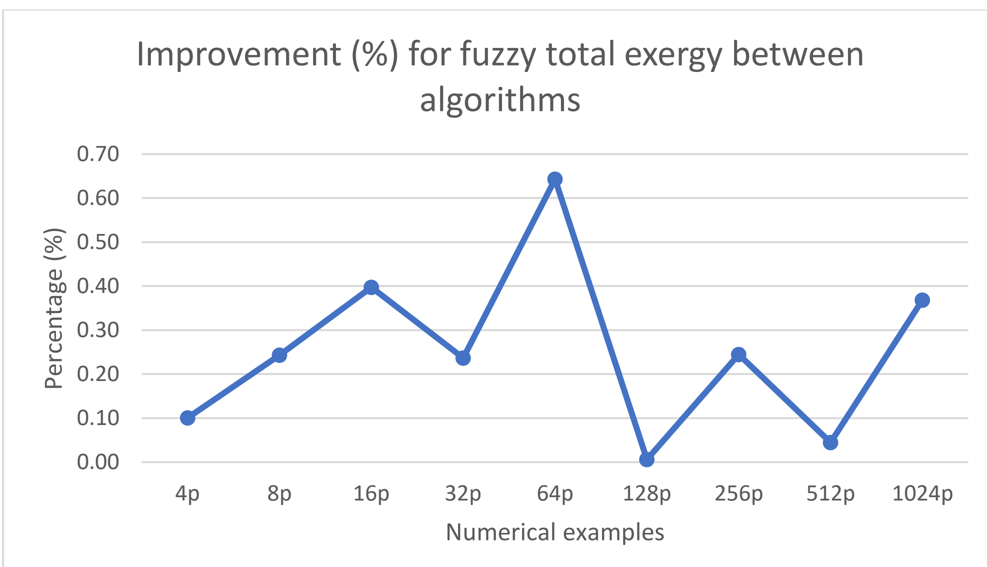

Fig.A.7.2. The fuzzy total exergy comparisons of two algorithms by percentage (Phase 2)

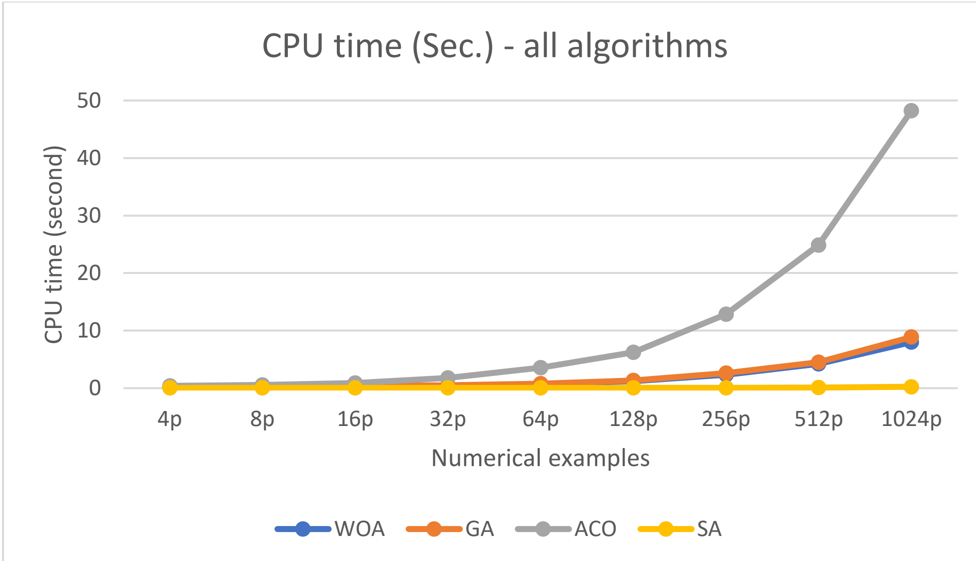

Fig.A.7.3. The CPU time comparisons of algorithms (Phase 2)

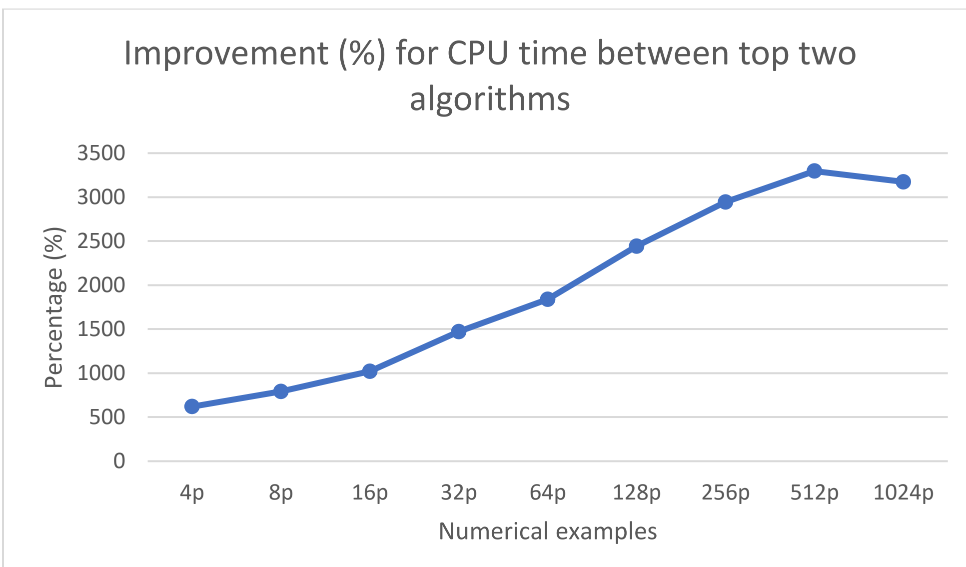

Fig.A.7.4. The improvement (%) of CPU time comparisons of the algorithms (Phase 2)

A.7.5.1.2. Part 2: *Find out the "exact" results and compare them with metaheuristic ones.*

In order to develop a good knowledge and understanding of the solution obtained through the suggested algorithms, a solution may be contrasted with an "exact method." This "exact result" can be achieved through an exact optimizer software such as "GAMS" or optimization library in "Python." Considering emission cap policy and Eq. (7.17) for a 4-item numerical example, the exact result (by GAMS) for the fuzzy total exergy is 715,249.78 (MJ), while the outcome of the best metaheuristic algorithm (GA) for this example is 734,740.68 (MJ). Consequently, the difference between them is 19,490.90 (MJ), and the percentage penalty or error is 2.72%. Since the percentage penalty is minor, this signals the good superiority of the solutions found through the best-suggested algorithm (Cárdenas-Barrón et al. 2012), as it is very close to the exact method (see Table A.7.1, and Fig. A.7.5). Regarding CPU running time, the difference between exact method time and GA is 4.046 (Sec.), while the percentage penalty is 1641.671%. It means the metaheuristic algorithm (GA) solved the cap policy model more quickly (see Table A.7.2 and Fig. A.7.6). Moreover, the example diagrams of fuzzy total exergy by the suggested algorithms are presented in Fig. (A.7.7).

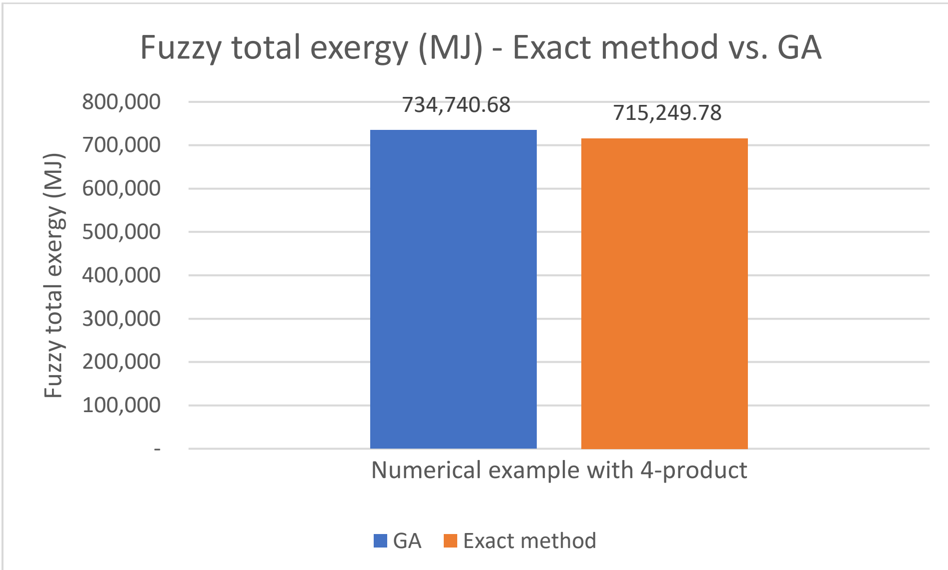

Fig.A.7.5. Comparison of the total fuzzy exergy between exact method and the best metaheuristic algorithm (Phase 3)

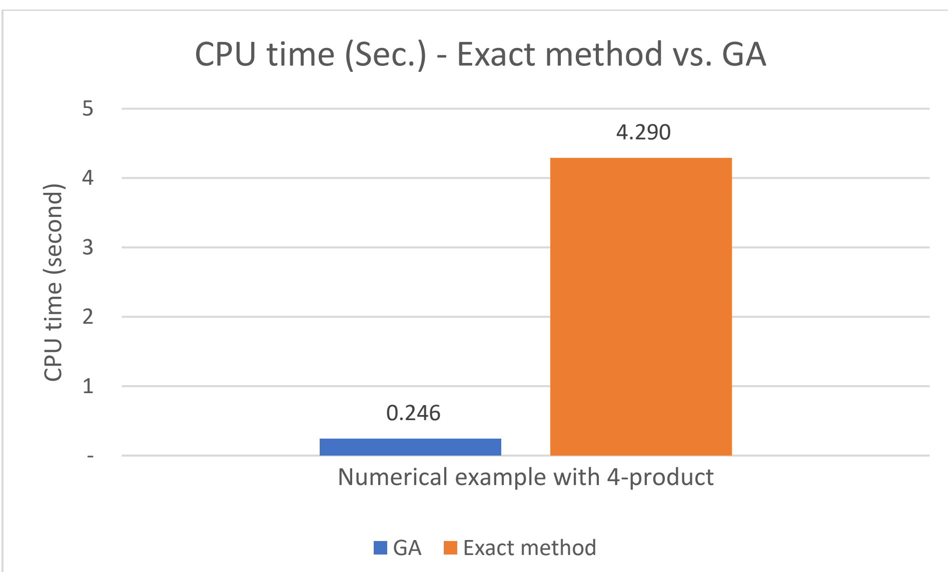

Fig.A.7.6. Compare CPU time between exact method and the best metaheuristic algorithm (Phase 3)

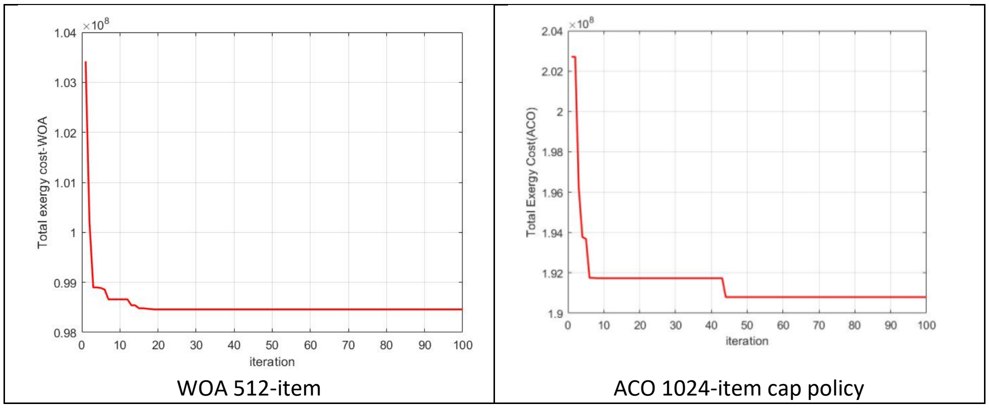

Fig.A.7.7. The diagrams of fuzzy total exergy by the suggested algorithms (Phases 2 & 3)

*A.7.5.1.3. **Part 3:** A sensitivity analysis of different percentages for exergy costs in five countries.*

In the previous subsections, we looked to optimize a sustainable inventory model of coal SC in Iran by considering different objectives simultaneously: the total inventory cost, the total cost associated with the additional required budget of all buyers, penalty cost of coal wastes disposal to the environment, and the whole carbon produced by coal SC. All goals in the model and related limitations under emission cap policy are in MJ instead of monetary values. In this phase, we go further and balance financial and sustainable benefits for coal SC enterprises. As our proposed models are sustainable, we are looking to adjust the exergy percentage for capital, labor, and environmental remediation by a sensitivity analysis to decrease the fuzzy total exergy more than before. Moreover, to get more insight into this issue, we compare the sensitivity analysis of a coal SC in Iran with two neighboring countries (Turkey and Afghanistan) in the Middle East and two developed countries in Europe and North America (Germany and Canada). We assume the same coal SC and items for all five countries. It was assumed that each cost $A_{i,S}, A_{ij,b},\ h_{ij}\ and\ C_i$ could be allocated to *Cap*=30% for money, *L*=60% for labor, and *Env.*=10% for ecological remediation. Now, in this section, these percentages are changed into five different sets (A-E) in Table A.7.3, and the fuzzy total exergy is obtained for a 4-item test problem under emission cap policy using the best-suggested algorithms. Moreover, the exergetic parameters used for five countries are the same as in Chapter 5.

Table A.7.3: Sensitivity analysis of different percentages for exergy costs (example with four items)-Carbon cap

%(Cap-L-Env)		Fuzzy total exergy (MJ)					Min.	Country min.	Max.	Country max.
		AF*	**CA**	**GE**	**IR**	**TR**				
Set A	**30-60-10**	141,316.53	3,269,610.51	3,216,971.32	734,828.56	2,972,014.13	141,316.53	AF	3,269,610.51	CA
Set B	**50-30-20**	164,919.79	1,285,976.37	1,192,900.68	854,814.77	3,256,774.91	164,919.79	AF	3,256,774.91	TR
Set C	**20-50-30**	146,451.08	3,268,083.12	3,048,417.64	761,440.02	3,032,929.71	146,451.08	AF	3,268,083.12	CA
Set D	**30-20-50**	174,187.82	666,924.42	600,277.13	901,519.42	3,368,441.83	174,187.82	AF	3,368,441.83	TR
Set E	**33-33-33**	161,779.26	1,555,685.52	1,528,691.42	838,931.07	3,219,102.84	161,779.26	AF	3,219,102.84	TR
Balanced point	**Min.**	**141,316.53**	**666,924.42**	**600,277.13**	**734,828.56**	**2,972,014.13**	Min. Min.		Max. Max.	
	Set min.	**A**	**D**	**D**	**A**	**A**	141,316.53	AF	3,368,441.83	TR
	Max.	174,187.82	3,269,610.51	3,216,971.32	901,519.42	3,368,441.83	Set A		Set D	
	Set max.	D	A	A	D	D				

*AF: Afghanistan, CA: Canada, GE: Germany, IR: Iran, TR: Turkey

A.7.5.1.3.1 Analysis of each country-Carbon cap

Considering Table 7.3 and Fig. 7.8, for coal supply chain in each country, we have:

- **Afghanistan:** As a developing country in the Middle East, the top exergy set are Set A (30-60-10), as Labor takes 60% while Environment holds only 10%. It generated the least fuzzy total exergy of 141,316.53 (MJ). The worst exergy set in Afghanistan is Set D (30-20-50), whilst 50% weight is assigned to Environment, which presented the maximum fuzzy total exergy of 174,187.82 (MJ).
- **Canada:** As a developed country in North America, the top exergy set in Canada is Set D (30-20-50), whereas more exergy percentage is offered to Environment (50%). It created the minimum amount of fuzzy total exergy with 666,924.42 (MJ) for coal supply chain. In the same way, the weakest exergy components are Set A (30-60-10) once more weight is given to the Labor (50%), which generated the greatest fuzzy total exergy of 3,269,610.51 (MJ).
- **Iran:** Like Afghanistan, the best exergy components ae Set A (30-60-10), as Labor gets 60% while Environment gets only 10%. It created the smallest fuzzy total exergy of 734,828.56 (MJ). The worst exergy elements in Iran are Set D (30-20-50), whilst 50% weight is assigned to Environment, which stated the maximum fuzzy total exergy of 901,519.42 (MJ).
- **Turkey:** Similar to Iran and Afghanistan, the top exergy elements in Turkey are Set A (30-60-10), whereas more exergy percentage is offered to Labor (60%). It created the minimum amount of fuzzy total exergy with 2,972,014.13 (MJ) for coal supply chain. Equally, the weakest exergy components are Set D (30-20-50) once more weight is given to the Environment (50%), which generated the greatest fuzzy total exergy of 3,368,441.83 (MJ).
- **Germany:** Different from the previous countries in the middle east, the most excellent exergy elements in Germany are Set D (30-20-50), after 50% of weight is allocated to Environment. It delivered the minimum fuzzy total exergy of 600,277.13 (MJ) for coal supply chain. Furthermore, the unhealthiest exergy components are Set A (30-60-10) when 60% weight is appointed to Labor, which composed the highest fuzzy total exergy of 3,216,971.32 (MJ).
- Concerning Table 7.3 and Fig. 7.8, the lowest amount of total exergy (MJ) in coal supply chain of each country is as follow Afghanistan (141,316.53), Canada (666,924.42), Iran (734,828.56), Turkey (2,972,014.13), and Germany (600,277.13).
- Among all given countries, the coal supply chain in Afghanistan has the lowest total exergy (141,316.53 MJ), followed by Canada, Germany, Iran, and Turkey, respectively (see Fig. 7.8). It is observed that coal SC in developed countries like Canada and Germany are more sustainable (less total exergy in MJ) than developing countries like Iran and Turkey. Sustainability performance of Coal SC in Afghanistan are an exceptional example among all presented countries.
- Moreover, coal supply chain in Turkey generates the maximum total exergy under exergy Sets of B (50-30-20), D (30-20-50) and E (33-33-33), among other countries. Likewise, Canada, under exergy Sets of A (30-60-10) and C (20-50-30), establishes the highest total exergy in coal supply chain (see Table 7.3).

A.7.5.1.3.2 Analysis of each exergy set-Carbon cap

Respecting Table 7.3 and Fig. 7.9, for each exergy set, we have:

- **Exergy Set A (30%-60%-10%):** In this set, more weight is assigned to Labor (60%) and only 10% to Environment. Although this set works well for coal supply chain in Afghanistan, Iran and Turkey, with the minimum total exergy of 141,316.53, 734,828.56 and 2,972,014.13 (MJ), respectively, Canada and Germany have a huge total exergy with 3,269,610.51 and 3,216,971.32 (MJ), respectively.
- **Exergy Set B (50%-30%-20%):** In this set, more weight is assumed for Capital (50%) along with Labor (30%) and Environment (20%), respectively. Regardless of coal supply chain in Turkey (3,256,774.91 MJ), exergy set B operates well in Afghanistan with 164,919.79 (MJ).
- **Exergy Set C (20%-50%-30%):** In this set, Labor has 50% weight, followed by Environment (30%) and Capital (20%), respectively. Exergy set C performs well in coal supply chain in Afghanistan (146,451.08 MJ), even though in Canada, the total exergy is a huge amount of 3,268,083.12 (MJ).
- **Exergy Set D (30%-20%-50%):** In this set, Labor has only 20% while 50% is for Environment. Despite the high result in Afghanistan (174,187.82 MJ), Iran (901,519.42 MJ) and Turkey (3,368,441.83 MJ), exergy set D runs well in Canada and Germany with 666,924.42 and 600,277.13 (MJ), respectively.
- **Exergy Set E (33%-33%-33%):** In this set, all three exergy components have equal 33% weight. Although exergy set E does not perform well in Turkey (3,219,102.84 MJ), it runs well in Afghanistan with 161,779.26 (MJ).
- Moreover, all exergy Sets (A-E) generated the minimum total exergy for coal supply chain in Afghanistan (see Fig. 7.9).

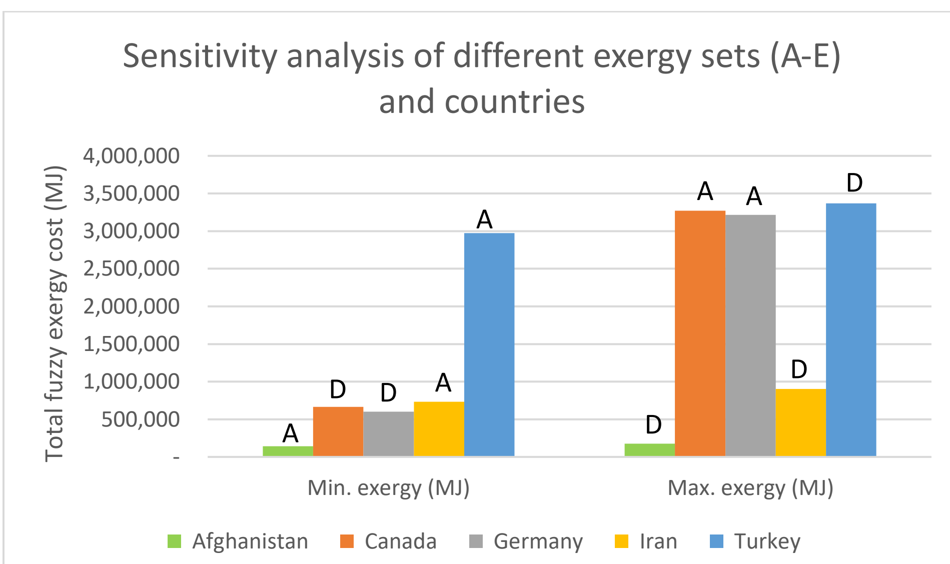

Fig.7.8. Sensitivity analysis - Min. and Max. of countries (Phase 4) -Carbon cap

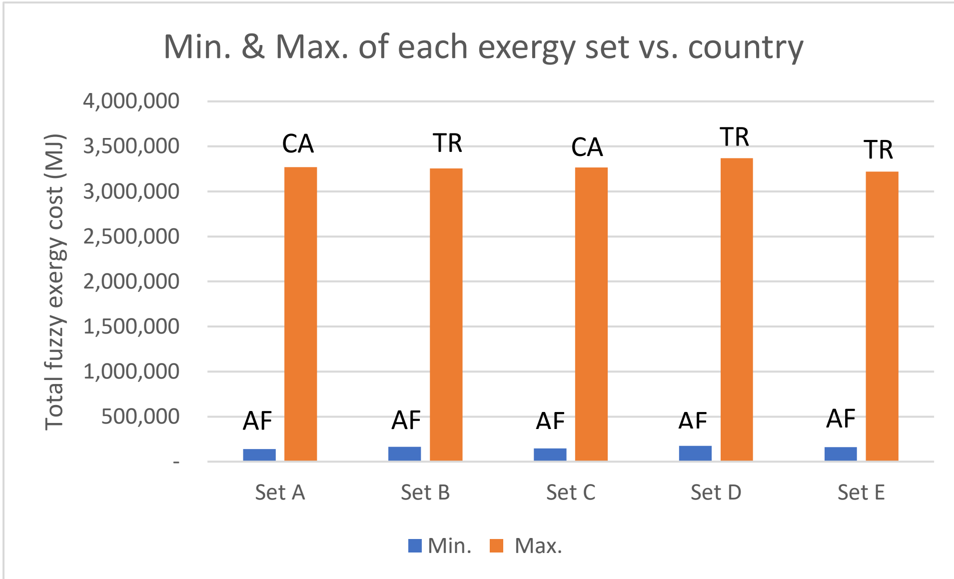

Fig.7.9. Sensitivity analysis of different exergy set vs. countries (Phase 4) -Carbon cap

Appendix 2. The results of carbon offset policy for the model (in chapter 8)

A.8.5.1.2 Step one - Metaheuristic algorithms (carbon offset)

Based on the solution procedure, in the first step, all suggested metaheuristic algorithms are executed 15 times for the fuzzy exergy model with carbon offset policy (Eq. 8.18). The outputs of algorithms include the lowest fuzzy total exergy (*MJ*), and the CPU times (*seconds*) are presented in Tables A.8.1 and A.8.2, respectively. Based on the results, the superior metaheuristic algorithm for the smallest fuzzy total exergy (*MJ*) and running times (*seconds*) could be found for the model (Eq. 8.18).

Concerning the fuzzy total exergy and in line with the fallouts shown in Table A.8.1, ALO is the best algorithm for 4-item (case study in Iran) and 10-item test problems with 41,699,351.48 and 192,815,840.24 (MJ), respectively. In contrast, for test problems from 20 to 2560 products, WOA is the best algorithm. For our large size test problems (640, 1280 & 2560 products), WOA gets the lowest fuzzy total exergy cost (8,738,009,828.86; 11,473,398,840.59 & 26,834,597,657.96 MJ) followed by LOA, and ALO, respectively (see Fig. A.8.1). Regarding Fig. A.8.2, performance improvement between top two algorithms from 20p to 80p test problems, are less since the results of them are very close together. But in large-size test problems the average performance enhancement between the results of WOA and LOA is about 67%, which means the results of WOA are outstanding. In opposition, ALO has the highest fuzzy total exergy (MJ) results in our medium and large-size test problems.

Considering the CPU time (Sec.), WOA is absolutely the best algorithm with the lowest running time in all test problems (see Fig. A.8.3). For example, in our large-size test problems (640, 1280 & 2560 products), the WOA CPU times were 46.86, 87.58, and 145.32 (Sec.), respectively (see Table A.8.2). Moreover, in large-size test problems, the average of WOA's performance improvement (%) with the second-best algorithm is about 794% which means WOA solves the models fast (see Fig. A.8.4). Conversely, ALO has the highest CPU time among other algorithms in all test problems except for 1285 products, where LOA (with 854.21 Sec.) is the worse algorithm (see Table A.8.2).

Table A.8.1: The fuzzy total exergy (MJ) observed by the algorithms under carbon offset policy in Iran (Eq. 8.18)

Test	ALO	LOA	WOA	Min. (MJ)	The bests	Performance improvement (%)
4p	41,699,351.48	65,557,736.94	57,974,289.79	41,699,351.48	ALO-WOA-LOA	39.03
10p	192,815,840.24	330,407,965.03	814,048,679.77	192,815,840.24	ALO-WOA-LOA	322.19
20p	1,329,753,409.64	943,464,336.09	916,902,967.07	916,902,967.07	WOA-LOA-ALO	2.90
40p	1,315,513,174.28	689,596,253.44	644,157,568.30	644,157,568.30	WOA-LOA-ALO	7.05
80p	2,862,253,819.39	1,015,340,034.70	1,002,634,912.33	1,002,634,912.33	WOA-LOA-ALO	1.27
160p	6,686,750,749.21	2,697,200,811.93	1,279,681,958.47	1,279,681,958.47	WOA-LOA-ALO	110.77
320p	12,886,852,130.10	7,374,089,405.06	4,002,255,616.45	4,002,255,616.45	WOA-LOA-ALO	84.25
640p	28,115,754,736.98	10,802,130,855.90	8,738,009,828.86	8,738,009,828.86	WOA-LOA-ALO	23.62
1280p	58,806,441,385.80	18,589,816,709.61	11,473,398,840.59	11,473,398,840.59	WOA-LOA-ALO	62.03
2560p	112,359,058,231.92	57,909,352,141.47	26,834,597,657.96	26,834,597,657.96	WOA-LOA-ALO	115.80

Table A.8.2: The CPU times (Sec.) of solving numerical examples by the algorithms under carbon offset policy in Iran (Eq. 8.18)

Test	ALO	LOA	WOA	Min. (Sec.)	The bests	Performance improvement (%)
4p	2.92	3.28	1.11	1.11	WOA-ALO-LOA	162.51
10p	8.43	7.21	1.44	1.44	WOA-LOA-ALO	400.22
20p	14.36	12.62	2.62	2.62	WOA-LOA-ALO	381.56
40p	27.76	26.46	4.26	4.26	WOA-LOA-ALO	520.74
80p	52.69	51.54	4.72	4.72	WOA-LOA-ALO	991.21
160p	104.94	85.52	7.84	7.84	WOA-LOA-ALO	990.08
320p	195.52	174.55	20.75	20.75	WOA-LOA-ALO	741.26
640p	397.71	370.71	46.86	46.86	WOA-LOA-ALO	691.05
1280p	841.25	854.21	87.58	87.58	WOA-ALO-LOA	860.60
2560p	1,595.56	1,353.21	145.32	145.32	WOA-LOA-ALO	831.16

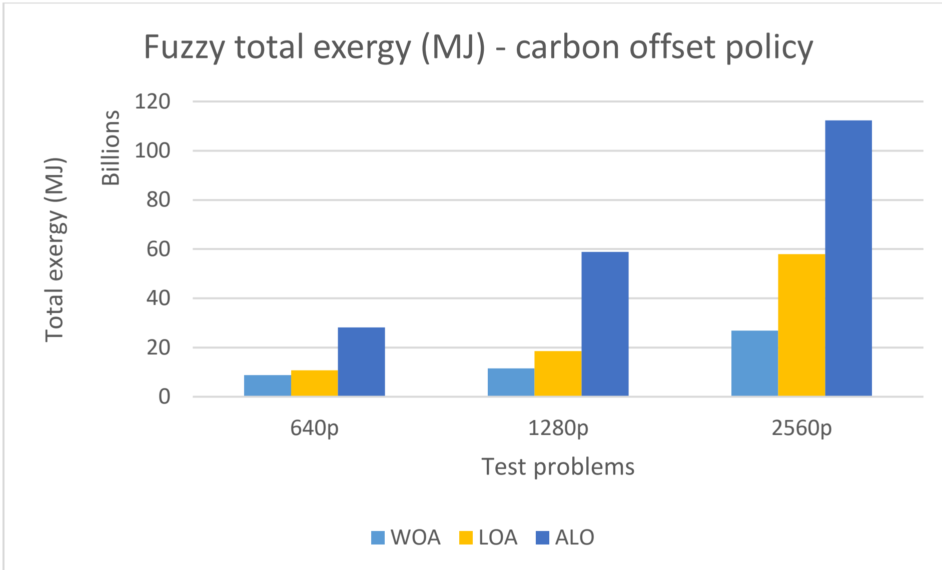

Fig.A.8.1. The total fuzzy exergy comparisons of algorithms in large size test problems (step 1)

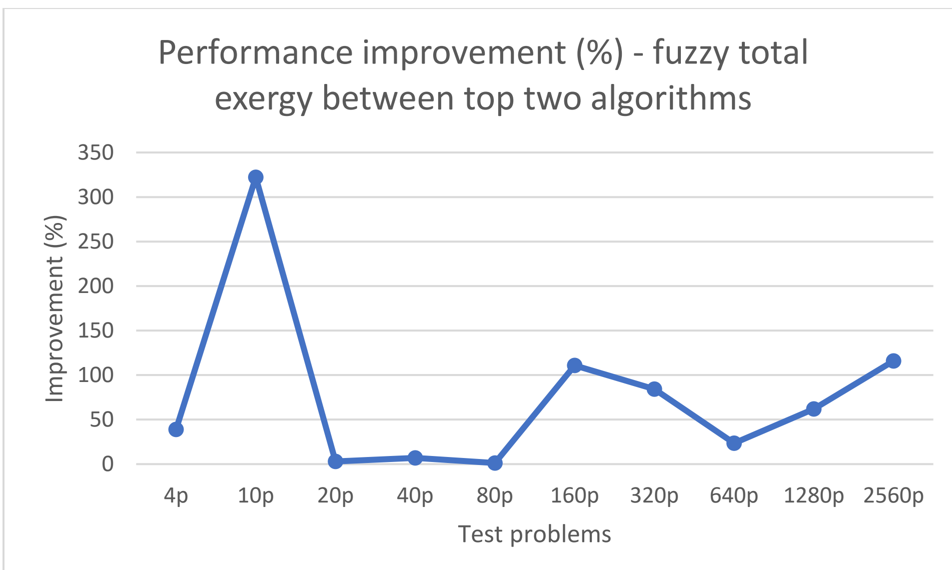

Fig.A.8.2. Performance improvement of top two algorithms for fuzzy total exergy (step 1)

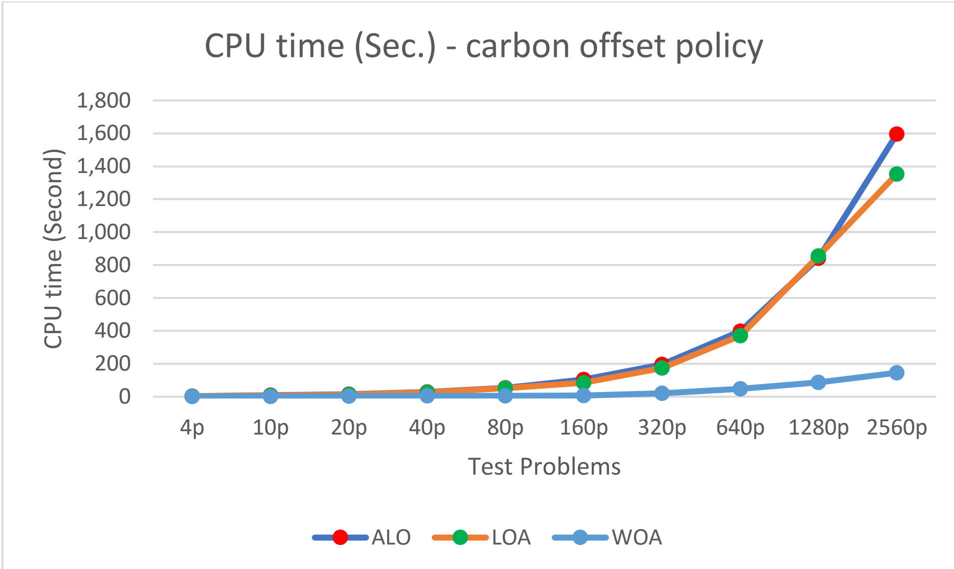

Fig.A.8.3. The CPU time comparisons of all algorithms (step 1)

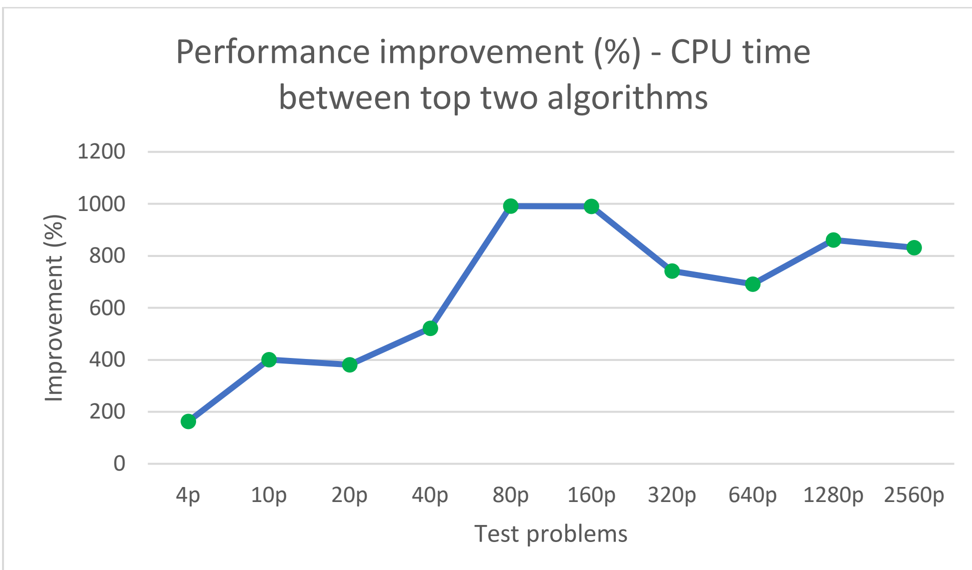

Fig.A.8.4. Performance improvement of top two algorithms for CPU time (step 1)

A.8.5.1.3 Step two - Exact method (carbon offset)

A solution may be compared with an "exact method" to validate the results by suggested algorithms. Exact optimizer software, for example, "GAMS" or an optimization library in "Python," can find the "exact result." In this research, the proposed mathematical model (Eq. 8.18) under carbon offset strategy is solved in small size (test with four products) by GAMS. A contrast with the best metaheuristic algorithm is made in Table A.8.3. Taking into account Eq. (8.18) for the 4-product test problem, the exact result for the fuzzy total exergy is 40,615,168.34 (MJ), while the outcome of the best metaheuristic algorithm (ALO) for this test is 41,699,351.48 (MJ). Therefore, the percentage penalty between the exact method and ALO is 2.67% (see Table A.8.3). Because the percentage penalty is minor, suggesting the excellent dominance of the solutions got by the best-suggested algorithm (Cárdenas-Barrón et al., 2012) since it is remarkably close to the exact method (see Fig. A.8.5). Concerning CPU running time, the distinction between exact method and ALO is 0.92 (Sec.), but the percentage penalty is 31.53%. It shows that the metaheuristic algorithm (ALO) solved the carbon offset model more rapidly (see Fig. A.8.6).

Table A.8.3: Comparing the results of the exact method (GAMS) with the best algorithm (ALO)

	ALO	Exact	Difference	Penalty (%)
Fuzzy total exergy:	41,699,351.48	40,615,168.34	1,084,183.14	2.67
CPU time:	2.92	3.84	0.92	31.53

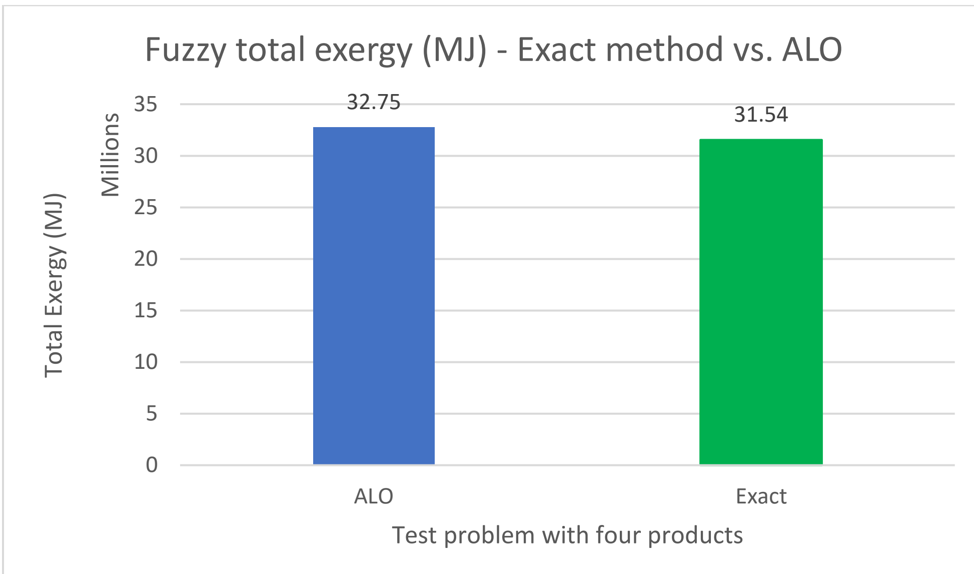

Fig.A.8.5. Comparison of the total fuzzy exergy between exact method and the best metaheuristic algorithm for test problem with four products (step 2)

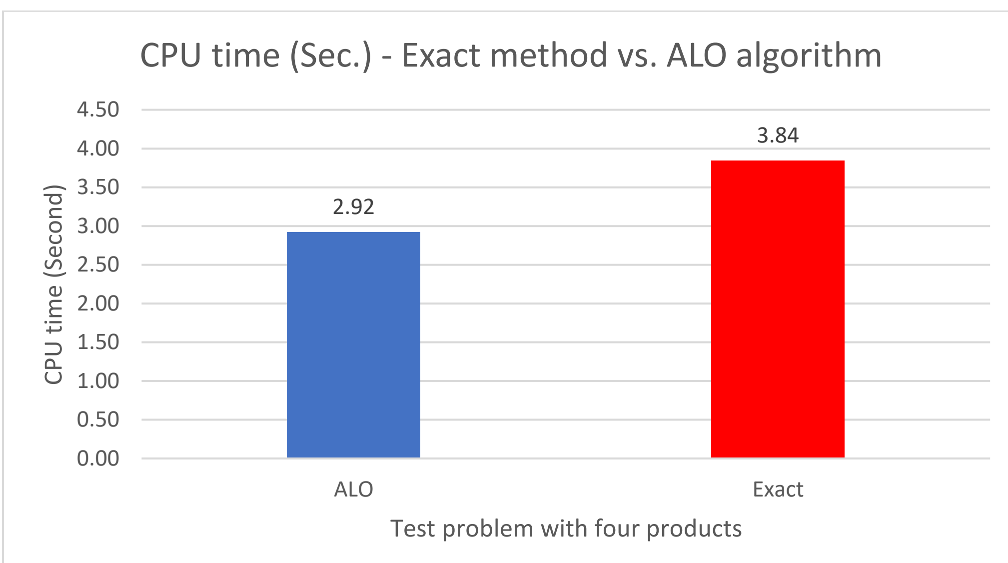

Fig.A.8.6. Comparison of the CPU time between exact method and the best metaheuristic algorithm for test problem with four products (step 2)

A.8.5.1.4 Step three- Sensitivity analysis (carbon offset)

In the earlier subsections, we studied the optimization of a sustainable fuzzy EPQ model of coal SC in Iran by taking into account different objectives simultaneously: the costs of the inventory system, an additional required budget of each buyer, coal transportation cost among SC members, and carbon emission cost. All goals in the models and related limitations under the emission offset strategy are in *MJ* in place of monetary values. This step tries to balance economic and sustainable advantages for coal SC companies. Considering that our proposed model is sustainable, we modify the exergy percentage for capital, labor, and environmental remediation by a sensitivity analysis to find the best values of exergy components that improve the sustainability of coal SC more than before. Additionally, to gain further insight into this adjustment, we evaluate sustainable coal SC in Iran as well as seven selected developing and developed countries with the world's most significant coal consumption. They are India, China, Australia, Japan, Poland, the USA, and Zimbabwe (Statista, 2020). We assumed the same coal SC and products for all these countries to make a comparative analysis. In the previous section, we mentioned that in our numerical examples, it was assumed that each cost of $K_{i,S}, K_{ij,b}, h_{ij}$ and C_i can be allocated to *Cap*=30% for capital, *L*=60% for labor, and *Env*=10% for ecological remediation (consider it as exergy Set A). In this section, to get more insight, we have changed these percentages to make seven different exergy sets (see Table A.8.4), including A (30-60-10), B (60-20-20), C (20-50-30), D (20-40-40), E (20-30-50), F (30-10-60) and G (33-33-33). Considering each exergy set, we computed the fuzzy total exergy for a 4-item test problem under carbon offset policy for all countries by GAMS (see Table A.8.4). For example, we consider coal SC in the USA and exergy Set C (*Cap*=20%, *L*=50%, and *Env*=30%), then employing extended exergy accounting method to convert all monetary costs of $K_{i,S}, K_{ij,b}, h_{ij}$ and C_i to equivalent (MJ). After that, we run model Eq. (8.18) with four product test problems using the Exact method (GAMS). Likewise, the same process was done for other exergy Sets (A-G) and considering other countries' coal SC. Finally, all results are presented in Table A.8.4. In the following section, we explain the results in detail.

Table A.8.4: Sensitivity analysis of different percentages for exergy elements (example with four products) -Carbon offset

Sets (%) *	Fuzzy total exergy (Emission offset) MJ								Min. (MJ)	Country min.	Max. (MJ)	Country max.
	AU**	CH	IN	IR	JA	PO	US	ZI				
A (30-60-10)	58,194,888.98	178,509,576.98	41,297,642.73	41,699,351.48	60,286,069.45	135,055,722.76	38,278,772.24	36,156,127.01	36,156,127.01	ZI	178,509,576.98	CH
B (60-20-20)	37,972,201.90	166,472,938.65	58,836,368.81	76,861,890.52	40,887,175.47	156,214,948.54	23,177,067.92	25,972,295.09	23,177,067.92	US	166,472,938.65	CH
C (20-50-30)	29,582,062.77	96,953,009.68	25,466,158.69	51,091,655.92	35,269,221.20	95,760,363.89	35,476,600.22	29,749,298.68	25,466,158.69	IN	96,953,009.68	CH
D (20-40-40)	50,525,851.36	156,133,267.82	47,301,831.54	50,771,812.85	40,123,715.86	124,452,996.38	39,435,137.75	25,914,513.09	25,914,513.09	ZI	156,133,267.82	CH
E (20-30-50)	37,058,048.28	161,309,694.66	45,946,885.83	48,215,183.84	38,498,459.38	135,883,311.16	26,724,522.66	33,867,997.48	26,724,522.66	US	161,309,694.66	CH
F (30-10-60)	25,381,554.37	153,294,716.80	49,637,349.70	66,584,735.15	27,876,026.26	147,446,020.63	21,032,559.94	24,119,890.07	21,032,559.94	US	153,294,716.80	CH
G (33-33-33)	36,154,500.20	136,870,365.31	38,479,371.31	71,932,762.38	35,790,111.54	146,622,025.05	33,876,380.99	31,260,609.82	31,260,609.82	ZI	146,622,025.05	PO
Min.	25,381,554.37	96,953,009.68	25,466,158.69	41,699,351.48	27,876,026.26	95,760,363.89	21,032,559.94	24,119,890.07	**Min. Min. (MJ)**		**Max. Max. (MJ)**	
Set Min.	F	C	C	A	F	C	F	F	21,032,559.94	USA	178,509,576.98	China
Max.	58,194,888.98	178,509,576.98	58,836,368.81	76,861,890.52	60,286,069.45	156,214,948.54	39,435,137.75	36,156,127.01				
Set Max.	A	A	B	B	A	B	D	A				

*Set (Cap%-L%-Environment%); **AU: Australia, CH: China, IN: India, IR: Iran, JA: Japan, PO: Poland, US: the USA, ZI: Zimbabwe

A.8.5.1.4.1 Analysis of each country-Carbon offset

Considering Table A.8.4 and Fig. A.8.7, for coal SC in each country, we have:

- **Australia:** The best sustainability condition for coal SC under the carbon offset policy in this country is with exergy Set F (30-10-60) since more exergy percentage is assumed for Environment (60%) and only 10% for Labor. It created the minimum fuzzy total exergy of 25,381,554.37 (MJ) for coal SC. Besides, the worst sustainability condition is by exergy Set A (30-60-10) since Labor has 60% while Environment has only 10%, which created the highest fuzzy total exergy with 58,194,888.98 (MJ).
- **China:** The exergy Set C (20-50-30) creates the top sustainability conditions for China when Labor has 50% weight, followed by Environment (30%) and Capital (20%), respectively. It created the minimum fuzzy total exergy of 96,953,009.68 (MJ) for coal SC. Like Australia, the weakest sustainability conditions are by exergy Set A (30-60-10) since Labor has 60% while Environment has only 10%. It generated the highest fuzzy total exergy of 178,509,576.98 (MJ).
- **India:** Like China, the finest sustainability condition is by exergy Set C (20-50-30), when Labor has 50% weight, while Environment and Capital are 30% and 20%, respectively. It produced the minimum fuzzy total exergy of 25,466,158.69 (MJ) for coal SC. Moreover, the unpleasant exergy components are Set B (60-20-20) when more weight is expected for Capital (60%) and the same weights (20%) for Labor and Environment, which formed the maximum fuzzy total exergy of 58,836,368.81 (MJ).
- **Iran:** For coal SC in this country, the top sustainability condition is by exergy Set A (30-60-10) as Labor has 60% while Environment has only 10%. It made the minimum fuzzy total exergy of 41,699,351.48 (MJ). Like India, the unhealthiest exergy components in Iran are Set B (60-20-20) when more weight is assigned to Capital (60%) and the same weights for Labor and Environment (20%), which generated the worst sustainability with maximum fuzzy total exergy of 76,861,890.52 (MJ).
- **Japan:** Like Australia, the best sustainability condition for coal SC in Japan is by exergy Set F (30-10-60), while more exergy percentage is given to Environment (60%) and less to Labor (10%). It established the least amount of fuzzy total exergy with 27,876,026.26 (MJ) for coal SC. Furthermore, like Australia and China, the unhealthiest sustainability condition is by exergy Set A (30-60-10) since Labor has 60% while Environment has only 10%, which generated the highest fuzzy total exergy of 60,286,069.45 (MJ).
- **Poland:** Like India and China, the excellent sustainability condition in Poland is by exergy Set C (20-50-30), when Labor has 50% weight, followed by Environment (30%) and Capital (20%), respectively. It created the least possible fuzzy total exergy of 95,760,363.89 (MJ) for coal SC. Besides, like India and Iran, the worst sustainability condition is by exergy Set B (60-20-20) when more weight is assigned to Capital (60%) and the same weights for Labor and Environment (20%), which created the maximum fuzzy total exergy of 156,214,948.54 (MJ).
- **The USA:** Like Australia and Japan, the superior sustainability condition in the USA is by exergy Set F (30-10-60) as more exergy percentage is assumed to Environment (60%) and less on Labor (10%). It generated the minimum fuzzy total exergy of 21,032,559.94 (MJ) for coal SC. Additionally, the harmful exergy components are Set D (20-40-40) since Labor and Environment have the same weights (40%) while Capital has only 20%, which established the highest fuzzy total exergy of 39,435,137.75 (MJ).

- **Zimbabwe:** Like Australia, Japan and the USA, the first-rate sustainability condition of coal SC in Zimbabwe is by exergy Set F (30-10-60) because more exergy percentage is assumed to Environment (60%) and less on Labor (10%). It crafted the minimum fuzzy total exergy of 24,119,890.07 (MJ). Additionally, like Australia, China and Japan, the worst weakest sustainability condition is by exergy Set A (30-60-10) since Labor has 60% while Environment has only 10%, which generated the greatest fuzzy total exergy of 36,156,127.01 (MJ).
- Considering Table A.8.4, the best total exergy (MJ) in each country is as follow: Australia (25,381,554.37), China (96,953,009.68), India (25,466,158.69), Iran (41,699,351.48), Japan (27,876,026.26), Poland (95,760,363.89), the USA (21,032,559.94) and Zimbabwe (24,119,890.07).
- Among all presented countries, the coal SC in the USA has the best sustainability condition (the smallest total exergy) with 21,032,559.94 MJ, followed by Zimbabwe, Australia, India, Japan, Iran, Poland, and China, respectively (see Fig. A.8.7).
- Moreover, coal SC in China creates the highest total exergy (the worst sustainability in MJ) for all exergy sets except for exergy Set G (33-33-33) related to Poland (see Fig. A.8.8).

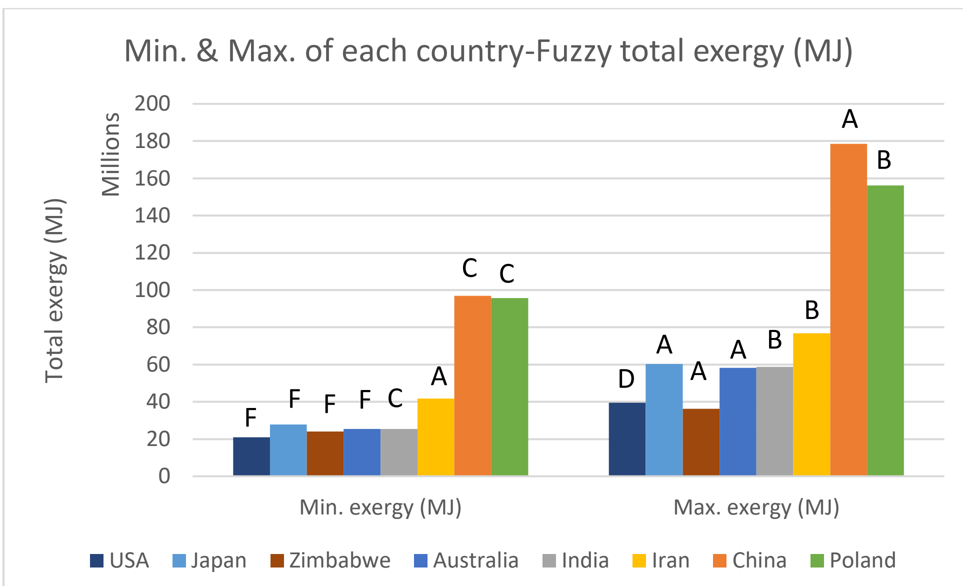

Fig.A.8.7. Sensitivity analysis for each country – Min. & Max. of the total fuzzy exergy (step 3)

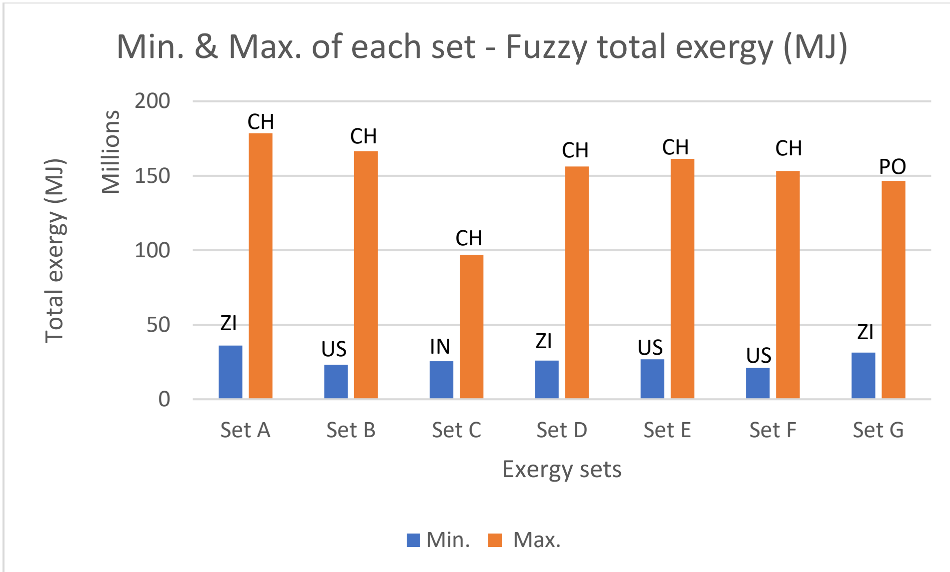

Fig.A.8.8. Sensitivity analysis for each set - Min. & Max. of the total fuzzy exergy (step 3)

A.8.5.1.4.2 Analysis of each exergy set-Carbon offset

Considering Table A.8.4, and Fig. A.8.8, for each exergy set, we have:

- **Exergy Set A (30%-60%-10%):** This exergy set has 60% weight for Labor, while for Environment, it is only 10%. Although this exergy set works well for coal SC in Zimbabwe with the most sustainable condition (the minimum total exergy) with 36,156,127.01 (MJ), in China, it creates the worst sustainable condition with 178,509,576.98 (MJ).
- **Exergy Set B (60%-20%-20%):** In this set, more weight is assumed for Capital (60%) and the same for Labor and Environment (20%). Despite the low sustainability condition in coal SC in China (166,472,938.65 MJ), exergy set B operates well in the USA with 23,177,067.92 (MJ).
- **Exergy Set C (20%-50%-30%):** In this set, Labor has 50% weight, followed by Environment (30%) and Capital (20%), respectively. Exergy set C performs well in terms of sustainability in coal SC in India (25,466,158.69 MJ), even though in China, the total exergy is a huge amount of 96,953,009.68 (MJ).
- **Exergy Set D (20%-40%-40%):** In this set, Capital has only 20% while 40% is for both Labor and Environment. Despite the high result (low sustainability) in China with 156,133,267.82 (MJ), exergy set D runs well in Zimbabwe with 25,914,513.09 (MJ).
- **Exergy Set E (20%-30%-50%):** In this set, 50% is assigned to Environment and 20% and 30% to Capital and Labor, respectively. Exergy set E operates well (with high sustainability) in the USA with 26,724,522.66 (MJ), although the result is worst coal SC in China (161,309,694.66 MJ).
- **Exergy Set F (30%-10%-60%):** In this set, 60% is allocated to Environment and only 10% Labor. Exergy set F creates top sustainability condition in the USA (21,032,559.94 MJ), even though the result is not healthy in China (153,294,716.80 MJ).
- **Exergy Set G (33%-33%-33%):** In this set, all three exergy components have equal 33% weight. Even though exergy set G does not perform well (with low sustainability condition) in Poland with 146,622,025.05 (MJ), it runs well in Zimbabwe with 31,260,609.82 (MJ).

- Moreover, exergy Sets B (30-60-10), E (20-30-50) and F (30-10-60) created the minimum total exergy for coal SC in the USA, while all exergy sets except Set G (33-33-33) created the highest total exergy (the lowest sustainability condition) in China (see Fig. A.8.8).

Appendix 3. The exergy parameters for all countries (Chapter 9)

Table A.9.1: The exergy parameters used in the inventory analysis of each country (Sciubba, 2011)

Country	α_x	β_x	ee_{Cap}(MJ/€)	ee_L(MJ/WH)
Afghanistan	0.0017	0.07	1.1	0.41
The USA	0.145	1.43	2.85	72.82
Canada	0.021	1.95	3.13	68.61
Germany	0.557	1.31	3.16	68.25
Zimbabwe	0.0026	3.9	3.35	70.18
Japan	0.773	1.9	3.35	70.18
Australia	0.018	1.69	3.56	71.21
India	0.0419	1.32	4.34	1.64
Iran	0.0121	2.94	5.68	3.56
China	0.0015	0.477	14.01	48.66
Poland	0.55	0.57	14.02	76.55
Turkey	0.411	1.35	20.51	91.36
Min.	0.0015	0.07	1.1	0.41
Country	China	Afghanistan	Afghanistan	Afghanistan
Max.	0.773	3.9	20.51	91.36
Country	Japan	Zimbabwe	Turkey	Turkey

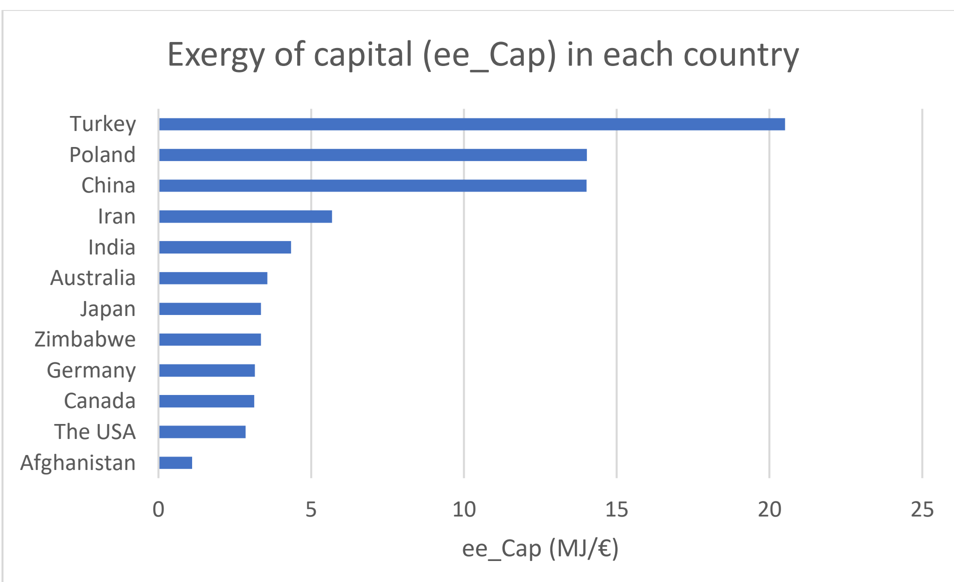

Fig. A.9.1. The exergy of Capital (ee_Cap) in developed and developing countries.