Enterprise, project and workforce selection models for Industry 4.0

Rupinder Kaur

A Thesis

In the

Concordia Institute for Information Systems Engineering (CIISE)

Presented in Partial Fulfillment of the Requirements for the Degree of Master of Applied Science

(Quality Systems Engineering)

Concordia University

Montreal, Quebec, Canada

August 2018

Concordia University

School of Graduate Studies

This is to certify that the thesis prepared by

By: Rupinder Kaur

Entitled: Enterprise, project and workforce selection models for Industry 4.0

and submitted in partial fulfillment of the requirements for the degree of

Master of Applied Science (Quality Systems Engineering)

Complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the final examining committee:

Dr. A. Youssef ____________ Chair

Dr. A. Awasthi ____________ Supervisor

Dr. A. Ben Hamza ____________ CIISE Examiner

Dr. R. Raut ____________ External Examiner (ECE)

Abstract

Enterprise, project, and workforce selection models for Industry 4.0.

Rupinder Kaur

The German federal government first coined industry 4.0 in 2011. Industry 4.0 involves the use of advanced technologies such as cyber-physical system, internet of things, cloud computing, and cognitive computing with the aim to revolutionize the current manufacturing practices. Automation and exchange of big data and key characteristics of Industry 4.0. Due to its numerous benefits, industries are readily investing in Industry 4.0, but this implementation is an uphill struggle.

In this thesis, we address three key problems related to Industry 4.0 implementation namely Enterprise selection, Project selection and Workforce selection. The first problem involves identification of enterprises suitable for Industry 4.0 implementation. The second problem involves prioritization and selection of Industry 4.0 projects for the chosen digital enterprises. The third and last problem involves workforce selection and assignment for execution of the identified Industry 4.0 projects. Multicriteria solution approaches based on TOPSIS and Genetic Algorithms are proposed to address these problems. Industry experts are involved to prioritize the criteria used for enterprise, project and workforce selection. Numerical applications are provided.

The proposed work is innovative and can be useful to manufacturing and service organizations interested in implementing Industry 4.0 projects for performance improvement.

Acknowledgements

As a matter of first importance, I would like to thank almighty God for giving me the chance to study in Concordia University. At that point, I might want to pass on my heartiest thanks to Dr. Anjali Awasthi for giving me the chance to learn under her direction. She has been unimaginably supportive. I am overwhelmed by the way she guided me all through the trip. Also, I want to thank my parents who have endeavored to give me the best environment for learning. I would also like to thank my closest companions Lovepreet kaur and Gurleen kaur for continually remaining close by. It is incogitable to find such favorites who have supported me on every step.

Table of Contents

List of Tables

List of Figures

List of Acronyms

CPS: Cyber Physical System

IOT: Internet of Things

PLC: Programmable Logical Controller

HMI: Human Machine Interaction

MES: Manufacturing Execution System

SIMMI: System Integration Maturity Model Industry

CBM: Cloud Based Manufacturing

RFID: radio frequency identification device

FTP: File Transfer Protocol

SOA: Service Oriented Architecture

ICT: Information and Communication Technology

ERP: Enterprise Resource Planning

CRM: Customer relationship management (CRM) systems

SCM: Supply chain management (SCM) systems

MOMA: Multi-skilling optimization model for allocation

MIP: Mixed integer programming

AHAMRS: Augmented heuristic algorithm for multi-skilled resource scheduling

PPS: Production planning systems (PPS)

DMS: Document management systems

MCDM: Multi Criteria Decision Making

MADM: Multi Attribute Decision Making

MODM: Multi Objective Decision Making

TOPSIS: The technique for order of preference by similarity to ideal solution.

SPC: Statistical Process Control

UML: Unified Modelling Language

AI: Artificial intelligence

GA: Genetic Algorithm

Chapter 1: Introduction

1.1 Context

With the amelioration in technology, there has been a tremendous increase in industrial productivity. From mechanization, electricity and information technology, we have reached to human robots today. In 2011 at Hannover fair event Germany introduced industry 4.0 which symbolizes the beginning of the fourth industrial revolution. With the use of internet of things and big data, industry 4.0 is approaching. Industry 4.0, a German strategic initiative, is aimed at creating intelligent factories where manufacturing technologies are upgraded and transformed by cyber-physical systems (CPSs), the internet of things (IOT) and cloud computing, (Zhong et al, 2017). According to Qin et al (2016), German engineers realise that manufacturing has been developed into a new paradigm shift, so-called 'Industry 4.0', where products tend to control their own manufacturing process. Since then, Industry 4.0 has become one of the most popular manufacturing topics among industry and academia in the world and has also been considered as the fourth industrial revolution with extreme impact on manufacturing in future. Due to numerous benefits, industries are readily investing in industry 4.0, but this implementation is an uphill struggle. It involves various factors to be considered especially when it is a small and medium scale industry. Following table depicts the different phases of development of industrialization:

	1st industrial revolution	**2nd industrial revolution**	**3rd industrial revolution**	**4th industrial revolution**
Time frame	1700's	1800's	1900's	2000's
Methods of production	By hand	Machine	Automation	• Self-optimization • Self-configuration • Self-diagnosis
Mass production	Textiles	Steel	Electronics	• Smart products • Smart factories • Artificial intelligence
Sources used	Water and steam	Electric energy	Transistors and microprocessors	• Cyber-physical system • internet of things
Invention	Spinning jenny Cotton gin	First assembly belt	First programmable logic controller	• Advanced robot • Additive manufacturing • Autonomous production • the cloud • Big data analytics • Augmented reality

Table 1-1. Industrial evolution

1.2 Thesis objective

The thesis has three main research objectives:

The first objective involves enterprise selection for the implementation of industry 4.0 projects. This involves identifying different factors to measure their readiness level industry 4.0 and prioritization.

The second objective involves Industry 4.0 project selection for the digital enterprise identified in step 1.

The third objective involves workforce planning and scheduling for the industry 4.0 project chosen in step 2.

It can be seen that these three objectives are inter-related and complementary to each other in successful implementation of industry 4.0.

1.3 Thesis outline

The rest of the thesis is organised as follows:

Chapter 2 presents the literature review on industry 4.0. Different evaluation criteria and models for enterprise selection, project selection and workforce selection are covered.

Chapter 3 presents the solution approaches. TOPSIS and GA based approaches are provided.

Chapter 4 presents the numerical application of the proposed approaches.

Chapter 4 provides the conclusions and gives directions for future studies.

Chapter 2:
Literature Review

2.1 Introduction

Introduction of industry 4.0 by Germany has completely driven the manufacturing phase to a new level. In this transformation interconnected systems with the help of sensors and automatic machines will enable the industry to accumulate the data at a single point so that they can utilize it in the best way. Consequently, it increases the productivity and profits of the companies. Many industries after visualizing the success of industry 4.0 in Germany are enthusiastically ready to implement industry 4.0. But the important question is how? What kind of factors is most important to them? This literature review is aimed towards industries with the help of which they can find out the important indicators for industry 4.0. Digital technology is the fundamental driving force for the fourth industrial revolution (Guoping et al., 2017). Following is the structural representation of this literature review.

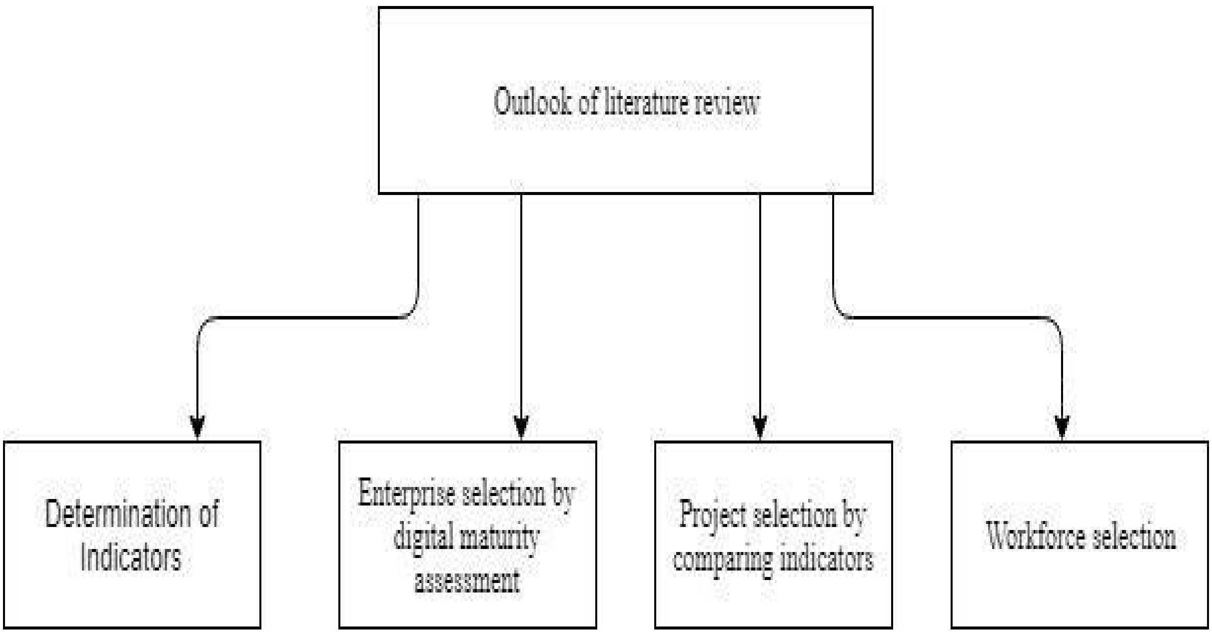


Figure 2-1. Structural representation of literature review.

2.2 Nine pillars of Industry 4.0

The criteria for enterprise selection are based on nine pillars of industry 4.0 which were proposed by Lorenz et al (2015),will completely change the manufacturing scenario. The individual parts will come together as an integrated, automated, and optimized production flow which in turn will increase the efficiency, productivity and will change the traditional production system. Lorenz et al (2015) proposed the nine pillars of industry 4.0 and their industrial and economic benefits for the manufacturers and production equipment suppliers. The importance given by an enterprise to these nine pillars is the key source to decide whether it is ready to implement industry 4.0. Various authors have described the nine pillars in their own way. Following are the nine pillars for industry 4.0:

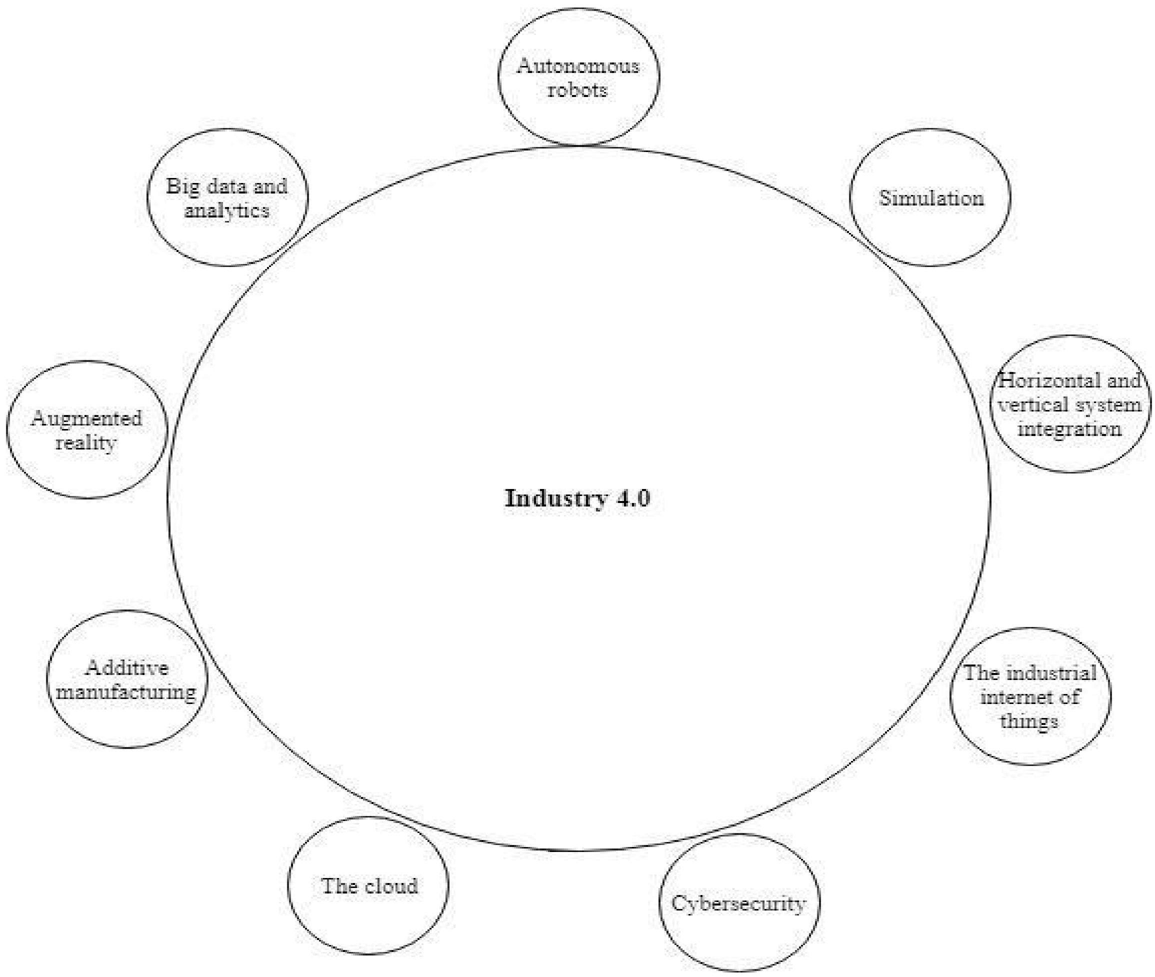


Figure 2-2. Nine pillars for industry 4.0 (Source: Markus Lorenz, 2015).

PwC's global industry 4.0 survey (2016) provides the detailed framework and contributing digital technologies in aerospace, defence and security. Due to internet of things (IOT) and cyber-physical system, there has been an exponential growth in data volume. Although there are many tools in market to solve the big data handling issues, but due to their complexities industries are resistant to use the tools. Kayabay et al (2016) presented a conceptual framework which offers higher level of abstraction to increase the adoption of big data techniques for industry 4.0. With this framework, organizations can implement industry 4.0 with ease. The internet transformation of the digital industry is still in progress, but artificial intelligence, big data and connectivity indicate the certainty of a new round of digital revolution (Roblek et al., 2016). Celaschi (2017) also described various technologies associated with the implementation of industry 4.0. Wittenberg (2016) discusses the effects of industry 4.0 on mobile applications for supporting service and maintenance technicians under the influence of the CPS/smart factories/industry 4.0. Gorecky et al (2014) described the introduction of new technologies like context-sensitive system and context-broker systems, due to the use of cyber-physical system in any industry. Also, change in human responsibilities due to the introduction of these new technologies are presented. Digital manufacturing incorporates technologies for the virtual representation of factories, buildings, machine systems equipment, labour staff and their skills, as well as for closer integration of product and process development through modelling and simulation (Mavrikios et al., 2009). SME's are the sector which needs to be developed using industry 4.0 concepts, especially in Europe so that it could be competitive to the global market (Nowotarski and Paslawski, 2017). Roughly 5% of SME's have adopted already the new disruptive technologies. However, just a third of them are creating strategies towards its full adoption as it takes the network of various IT systems and the infrastructure (Pereshybkina et al., 2017). Industry 4.0 involves the main technological innovations applied to production processes in the field of automation, control and information technologies. The way people interact with organizations, the data produced by organization's day by day activities and the rate at which the transactions occurs may create unprecedented challenges in data collection, storage, processing and analysis. This is also due to advancement in cloud computing, internet, mobile devices and embedded sensors (Santos et al., 2017).

2.3 Digital maturity assessment of enterprises

Industry 4.0 is a new concept for various organizations. Many organizations are hesitant to implement it t due to complexity and budget issues. However, some of the industries are highly advanced in the area and need not implement new strategies. There are various maturity models presented to measure the digitization level for any industry. One such example is SIMMI 4.0- System Integration Maturity Model Industry 4.0. In this model, Leyh et al (2016) used various interrogation techniques to figure out which information and enterprise systems are used in business (especially in SMEs) and in what shape the IT-infrastructure of the company may appear. In their research paper, they present the design of an IT landscape so that a company can "move" in the field of industry 4.0. Following figure presents their requirements for IT systems in the context of industry 4.0:

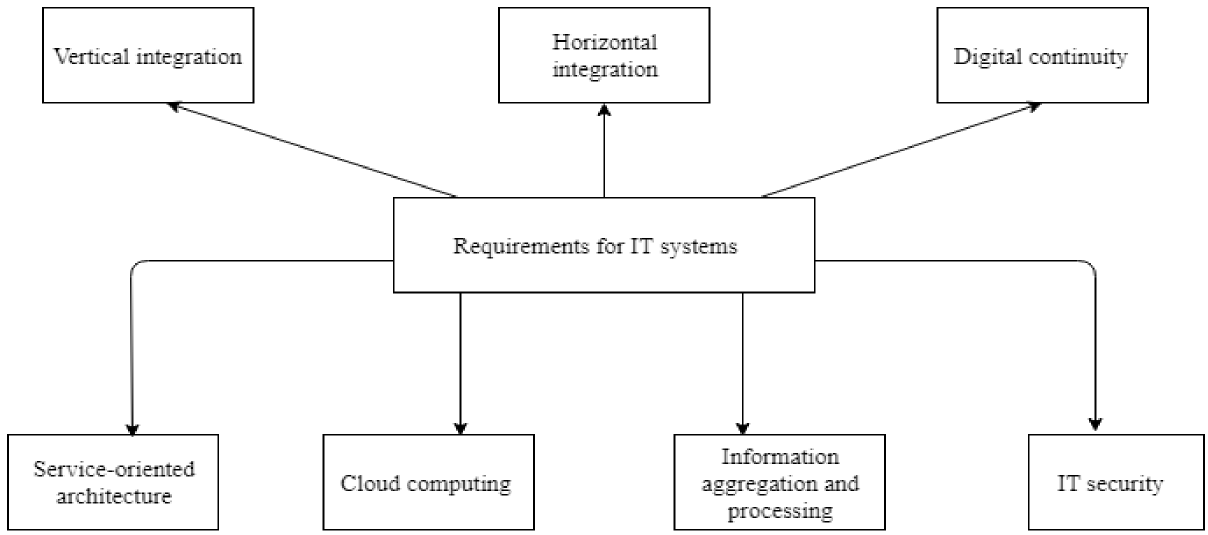


Figure 2-3. Requirements for IT systems (Source: Leyh et al., 2016)

These requirements are presented in detail as follows:

a) Digital Continuity:

Jin et al (2014) conducted a large-scale survey in U.S and analysed that IT enabled infrastructures provide various benefits like supply chain flexibility, production flexibility, logistics flexibility and supplier's flexibility. They analysed that with the help of IT systems, performance of any industry can be improved. Gunasekaran et al (2017) reviewed that IT has revolutionised traditional logistics and supply chains to achieve numerous benefits such as increased efficiency and responsiveness. With the help of the model they provided, the role of IT for competitive advantage within supply chains can be tested.

b) Horizontal and vertical integration:

With the help of IT in industry 4.0 we can visualize numerous benefits. Horizontal and vertical integration is one of those. With the help of IT, information is shared among each level. This vanish the boundaries and makes information available to every department and level. Supply chain integration is also the result of horizontal (external) and vertical (internal) integration. In Internal integration, the organization information sharing occurs across the various hierarchical levels of organization to enable joint planning and decision making (Wong et al., 2017). In external integration, information is shared across external members of an organization. They can be the suppliers, customers, distributors and retailers. It enables members to develop a good understanding of customer requirements which reduces design errors. A manufacturer can thus provide the customer with the reliable products (Zhang et al., 2017). Using IIoT or industrial internet of things, the product, the machine that manipulates it and the system of suppliers upstream and downstream of the production process interact and interfere, exchanging information useful for the improvement of the process itself. This is called vertical integration of information and is largely entrusted in the future to the so called "Cloudification" of the production process (Celaschi, 2017).

c) Service oriented architecture:

Zhiting et al (2017) propose that Servitization, when integrated into traditional manufacturing practices produces a new manufacturing technique called service-oriented manufacturing. With the advancement in horizontal and vertical integration due to industry 4.0, there has been tremendous increase in service-oriented manufacturing. Various technologies have ushered in service-oriented manufacturing phenomenon like cyber physical system, wireless sensor networks, cloud computing, internet of things and big data.

d) Cloud computing:

Cloud computing is a general term that refers to delivering computational services through visualized and scalable resources over the internet. Cloud manufacturing refers to an advanced manufacturing model under the support of cloud computing, virtualization and service-oriented technologies that convert manufacturing into services and resources which can be comprehensively shared and circulated, Xu et al (2017). Cloud-based manufacturing (CBM) is another rising paradigm that will significantly contribute to the success of industry 4.0. It can be described as networked manufacturing model that exploits on-demand access to a shared collection of diversified and distributed manufacturing resources to form temporary, reconfigurable, cyber physical production line which enhances efficiency, reduces product lifecycle costs, and allows for optimal resource allocation in response to variable-demand customer generated tasking (Thames et al, 2017). Additionally, in cloud manufacturing various production resources and capacities can be intelligently sensed and connected to the cloud, IoT technologies such as RFID and bar codes can be used to automatically manage and control these resources so that they can be digitalized for sharing. Service oriented technologies and cloud computing are the underpinning support for this concept (Xu et al., 2017).

e) IT security:

With the introduction of industry 4.0, a huge amount of data is shared and created. Thus, this data need to be secured in every form. There has been tremendous effort in recent years to cope with the security issues in the IOT paradigm. Some of these approaches target security issues at a specific layer, where as other approaches aim at providing end to end security for IoT (Salah et al, 2018). Othman et al (2017) described that to extensively adopt the IOT; the security issue should be addressed to provide user confidence in terms of privacy and control of personal information. The development of IoT greatly depends on addressing security concerns. They survey a wide range of existing works in IoT security that uses different techniques and presented a security taxonomy based on the current security threats in the context of application, architecture and communication. A new security scenario for the IoT structure and analysis of the possible threats and attack to the IOT environment was provided.

With the help of literature analysis, they derived four dimensions of SIMMI 4.0 based on the requirements mentioned above.

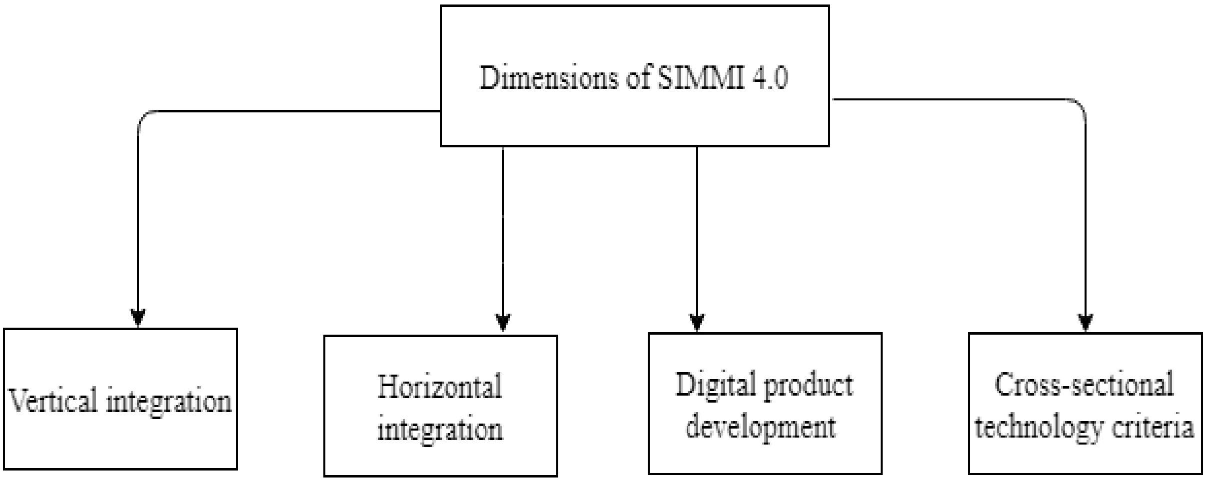


Figure 2-4. Dimensions of SIMMI 4.0 (Source: Othman et al., 2017).

Additionally, SIMMI can be achieved in 5 stages. Following are the five stages:

Stages	Achievement	Loop-holes
Stage 1: Basic digitization level	• With specially implemented and complex interfaces, integration is achieved	• Processes are not or partially digitized. • Does not pursue service-oriented and cloud-based approaches. • Data is not protected. • Continuous availability of data is not ensured.
Stage 2: Cross-departmental digitization	• Digitization implemented across departments. • Information can be partially exchanged automatically.	• Instead of cloud solutions production plants are connected through paper-based methods, email, FTP, etc. • The company starts to implement an SOA.
Stage 3: Horizontal and vertical digitization	• Establishment of an SOA. • Implementation of cloud principles to exchange information within the enterprise. • Advanced data security model and data encryption within the enterprise.	• Cloud-based platform to offer service across the company border.
Stage 4: full digitization	• Industry 4.0 approaches are actively followed and anchored within the corporate strategy. • Cloud-based platform.	• Beginning collaboration with companies within the value networks for end-to-end solutions and the optimization of information flows.
Stage 5: optimized full digitization	• Each step inside and outside is digitized. • IT security adjusts promptly to new risks.	• No loop-holes.

Table 2-1. Stages of SIMMI 4.0 (Source: Othman et al, 2017).

Industry 4.0 is the latest industry revolution that is completely transforming the manufacturing processes with the use of cyber-physical systems and internet of things (IOT). Consequently, academics and researchers have shown keen interest in working practices of industry 4.0, establishing the design principles for implementation of industry 4.0, understanding the key components and characteristics for analysing industry 4.0 readiness in emerging economies (Samaranayake et al, 2017). In 2014, Brettel et al proposed modular simulation and cluster analysis to measure the relevance of industry 4.0. The results reveal the reasons for the adaption and refusal of industry 4.0 from a managerial point of view. Modularization: it is an accepted mean to increase the variety of products by decoupling the architecture of the product in the subsystems but with little interdependencies so that the combinations of standardized modules can be adjusted flexibly. This in turn will increase the speed of development of new product and time to market can be reduced. Using cluster analysis, they analysed the following sub-topics from literature:

- Mass customization
- Modularization
- Flexible and reconfigurable manufacturing systems
- Distributed control
- Self- optimization
- Rapid manufacturing
- Cloud computing

Bley et al (2016) proposed a maturity model based on self –assessment of 239 companies regarding digitization and number of implemented enterprise systems. Many companies over estimate themselves in terms of information and communication technology or level of digitization. They designed the questionnaire to measure the self-perceived and actual level of digitization of companies. These misjudgements can be seen especially in the field of SMEs. They also provided the studies conducted by Deloitte (2013) showing the level of digitization of 41 SMEs and derived possible trends in this field. To determine the causes and effects of the digital transformation of German industries, the BDI in cooperation with Roland Berger (BDI and Roland Berger 2015) conducted different studies and concluded that companies realize the importance of digitization as digital transformation has arrived in the corporate world. But it is very important to understand the challenges and effects of digitization. Implementation of the opportunities arising from digitization is still not conducted. The questions were divided into following categories:

- General information about the company
- Hardware and software utilization
- Internet and network
- ICT (information and communication technology)
- Further needs formulated by companies themselves

They were also asked to choose among the six major enterprises systems:

- ERP systems
- Customer relationship management (CRM) systems
- Supply chain management (SCM) systems
- Production planning systems (PPS)
- Document management systems (DMS)
- Social-CRM systems

Result: Based on results of companies following final results were determined:

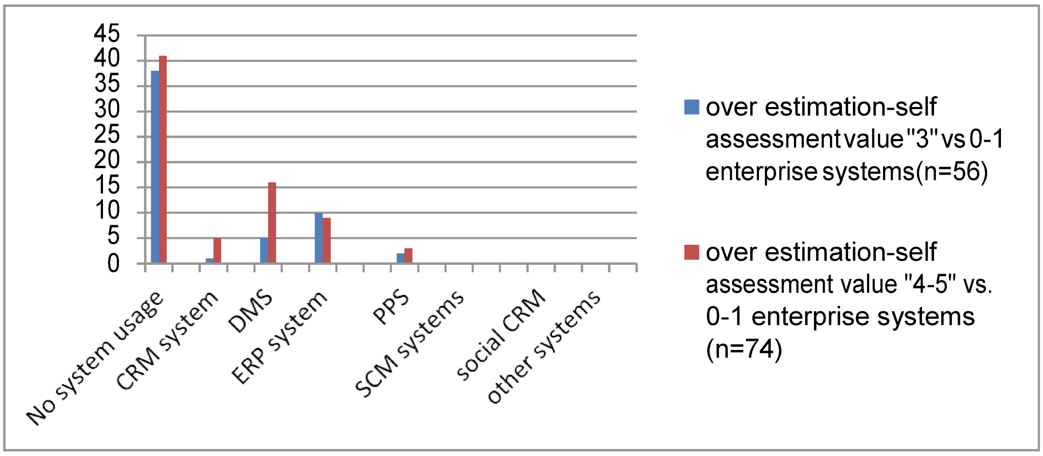


Figure 2-5. Detailed system uses vs. self-assessment of ICT use (Source: Bley et al, 2016).

Chen et al (2017) represented that ultimate goal of industry 4.0 can be achieved by the realization of digital factory which emphasizes on total integration with cyber-physical system as its core technology, via internet of things to realize the operational environment of human machine interaction and the utilization of big data for decision making. They described the sequence of machine movements controlled by programmable logic controller (PLC). The primary objective of this study was to determine the key elements of industry 4.0 and to investigate the role PLC played in digital factory to establish smart technologies. Future manufacturing processes will include more flexible production lines and faster machines that are more accurate, efficient, smarter, and offer a greater IT connectivity to ERP systems and manufacturing execution systems (Masdefiol and Stavmo, 2016).

Samaranayake et al (2017) identified the importance of key enabling factors for the implementation of industry 4.0 in enterprises from the technological readiness perspective. They prioritize the dimensions using the AHP technique. This research methodology is conducted using two stages.

- For the first stage, they determine the factors which reflect the technological readiness perspective using the literature review. Potential factors for the implementation of industry 4.0 can vary depending upon the size of the organization
- In the second stage, Q-sort techniques are used for the validation of the factors obtained in stage 1.
- Based on the systematic review, a review panel of eight experts selected from industry found the potential factors for the implementation of industry 4.0 and grouped them into following dimensions:

Technological readiness	Enabling factors for implementation of industry 4.0
Dimension 1(D1): Improve and develop the internet system	Stability of internet
	Promote business online
	Develop and improve online communication
Dimension 2(D2): Knowledge of human in technology and how to use it	Develop skill and ability in simulation systems
	Develop skill and ability of staff to use new technology and knowledge
	Improve knowledge, skills and abilities of data scientists
	Help technology development researchers
	Applying other knowledge to be used together e.g. science, technology, innovation, etc.
	Motivate staff in organisations to gain new knowledge
Dimension 3(D3): Improve ability of machine and device in connecting internet	Develop machine ability in order to use high technology e.g. connect with internet
	Develop low energy wireless sensors
	Develop receiving and sending data systems on device e.g. microchip or smart devices
	Improve and develop automation
Dimension 4(D4): Ability to manage the big data	Online data storage
	Storing complex data and big data
	Education about data management
Dimension 5(D5): Data sharing between or within organization	Cross-organisational cooperation
	Data sharing in value chain
	Promote industry 4.0 in manufacturing and trade association
Dimension 6(D6): Develop the data security system	Develop comprehensive security systems which cover human, data and environment

Table 2-2. Dimensions including the potential factors for the implementation of industry 4.0 (Source: Samaranayake et al., 2017).

- At the next phase, after 2-3 rounds of iterations from different experts selected from industry, Cohen's Kappa coefficients as a measure of agreement were evaluated. Cohen's Kappa coefficient (K) of at least 0.65 is considered as accepted level for construct validity. The results are shown in the following table:

Category	Kj	Var(Kj)	Kj/SE(Kj)
Total	0.79	0.0023774	16.1039880
D1	0.73	0.0109875	6.9543683
D2	0.83	0.0165068	6.4749927
D3	0.67	0.0146693	5.5634289
D4	0.85	0.0111901	8.0132490
D5	0.86	0.0116156	7.9589030
D6	0.79	0.0094388	8.0971671

Table 2-3. Cohen's Kappa coefficients (Source : Samaranayake et al., 2017).

- In the second stage, AHP was used to determine the relative weight of importance among six technological readiness dimensions to achieve industry 4.0 organisational performances. Considering the performance measure from the literature review and experts opinion on organisational performance relevant for industry 4.0, four performance measures were selected as key objective measures for evaluating the relative importance of six technological dimensions. Following results were obtained:

Alternatives	**Performance measures (Relative weighted score)**			
	Cost reduction (0.193)	Flexibility in production services (0.377)	Stability of process (0.340)	Reduce energy pollution (0.089)
D1: Improve and develop the internet system	6 (0.116)	4 (0.141)	3 (0.158)	6 (0.107)
D2: Knowledge of human in technology and how to use it	1 (0.294)	1 (0.256)	1 (0.261)	1 (0.243)
D3: Improve ability of machine and device in connecting internet	2 (0.208)	3 0.(173)	2 (0.178)	3 (0.190)
D4: Ability to manage the big data	5 (0.118)	2 (0.187)	4 (0.145)	4 (0.128)
D5: Data sharing between or within organization	3 (0.143)	5 (0.136)	6 (0.120)	2 (0.207)
D6: Develop the data security system	4 (0.120)	6 (0.106)	5 (0.139)	5 (0.126)

Table 2-4. Results of performance measures, Samaranayake et al (2017).

Results of AHP method shows that the most important objective in implementing (moving to industry 4.0) is the flexibility in production/service.

2.4 Industry 4.0 projects

In context of industry 4.0, projects can be found in reference to nine pillars of industry 4.0. These projects are really important for the implementation of industry 4.0. With the help of the references mentioned in enterprise section, following are the projects listed for any industry. These projects are for the fully digitized industries as these are the highly advanced technological developments.

Projects	**References**
Cloud manufacturing.	Industrie 4.0: Enabling Technologies, Wan et al.
Real time process.	Cyber-physcial Machine Tool-the era of machine tool 4.0, Liu et al.
Additive manufacturing.	The role of additive manufacturing in the era of industry 4.0, Dilberoglu et al.
Natural HMI.	Human-CPS interaction-requirements and human-machine interaction methods for the industry 4.0, Wittenberg et al. Human-machine-interaction in the industry 4.0 era, Gorecky et al.
Manufacturing execution system (MES).	Learning in the AutFab-the fully automated industrie 4.0 learning factory of the university of applied sciences Darmstadt, simons et al.
Cyber-security	Analysis of the Cyber-Security of industry 4.0 technologies based on RAMI 4.0 and identification of requirements, Flatt et al.
Collaborative robots.	Industry 4.0: the future productivity and growth in manufacturing industries, Rubmann et al.
Augmented reality and virtual reality.	Supporting remote maintenance in industry 4.0 through augmented reality, Masoni et al.
Big data & advanced analytics.	Advanced design-driven approaches for an industry 4.0 framework: The human-centred dimension of the digital industrial revolution, Celaschi et al.

Table 2-5. Industry 4.0 projects

2.5 Enterprise selection

2.5.1 Indicators (Criteria) for Enterprise selection

Based on research done by various authors, following criteria were obtained for measuring the readiness level of enterprises for Industry 4.0.

Criteria	**Sub-criteria**	**Author**
Technical expertise	• Number of ERP system used • Technological and knowledge management	Crispim and De souse (, 2009)
		Wu and Barnes (2010)
Organizational structure	• Inter-enterprise structure • Industrial and organizational competitiveness	Verdecho et al. (2011)
		Wu and Barnes (2010)
Cost and budget	For raw material and production	Wu and Barnes (2011)
Quality and services	Materials used, and products manufactured	Sha and Che (2004)
Logistics	Automated and updated	Sarkis et al. (2007)

Table 2-6. Criteria for enterprise selection.

Note that the criteria will vary depending on the digital readiness level of organizations.

Criteria	Sub-categories	Author
Basic digitization level	Information systems or ERP systems	Othman et al, 2017
Cross-departmental organization	IOT Improve ability of machine and device in connecting internet	FitzHugh and Piercy, 2013
Horizontal and vertical integration	Automated machines	Celaschi et al, 2017
Full digitization	Inter-organizational network Cloud computing	Kagermann, 2014
Advanced level of digitization	Autonomous manufacturing	Jin et al, 2014 Gunasekaran et al,2017 Xu et al, 2017

Table 2-7. Criteria for implementation of industry 4.0

2.5.2 Methods for enterprise selection

Table below presents the evaluation methods for selection of enterprises for IT projects.

Method	Author
AHP	Sari et al. (2008)
Hybrid SWARA and VIKOR	Alimardani et al. (2013)
Data envelopment analysis and analytical network process.	Hasan et al. (2008)
ANP	Sarkis et al. (2007)
dynamic feedback model, Dempster-Shafer theory, RBF-ANN, ANP-MIMOP	Wu and Barnes (2012)
Fuzzy TOPSIS	Crispim and de Sousa (2009)
Dempster–Shafer belief acceptability optimisation	Wu and Barnes (2010)
Analytic network process-mixed integer multi-objective programming	Wu et al. (2009)
Analytic hierarchy process (AHP) methodology, multi-attribute utility theory (MAUT) and integer programming (IP)	Sha and Che (2005)
ANP	Verdecho et al. (2012)

Table2-8. Methods used for enterprise selection.

2.6 Project selection

2.6.1 Criteria for project selection

According to Amiri (2010), the evaluation and selection of projects before investment decision is customarily done using technical information. In a world of limited resources choices have to be made. It is not important that every project has a viability. And amongst those that do, limited resources like people, time, money and equipment must be applied judicially. With the help of the maturity models', industries can realize their level of digitization, but now next step is to choose the high priority indicators. It is easy to determine the projects for any industry, but the difficult process is to prioritize these projects because all these projects need a large budget for the implementation. So, it is very important to recognize which one to implement first.

The criteria for the selection of project are on the basis of the nine pillars defined for industry 4.0 and other factors like cost, time and many more. It is very important to select the criteria for the project selection. In the selection of project, the prioritization of indicators is really important. So far, industries find it really hard when transforming the visionary ideas to missionary level of increasing the productivity. An isolated implementation of the industry 4.0 visions could be the reason (e.g. implementation of 3D printing). Collaborative productivity in the industries can be achieved practically, only with the collaborative implementation of all the concepts of industry 4.0 (Erol et al, 2016). So, it is very important to implement these indicators. But the implementation of these indicators together can result in a huge business for small and medium scale industries. Thus, importance by paid by the industry to these indicators can help in prioritizing the indicators and then they can be implemented accordingly. Following criteria can be adopted for the project selection:

Figure 2-6 Three step method for project selection.

The benefits of harnessing the yields of industry 4.0 are also diversified. The integration of physical objects, human interactions, intelligent machines, processes, and production lines results into the development of a new, intelligent, connected, and efficient value chain which enables the development of new business models with different organizations (Fettermann et al., 2018).

Following tables describes sample Industry 4.0 projects and associated criteria reported in literature for the selection of a project.

Area	**Project**
Technology	ERP IIOT Cloud computing
Advance manufacturing components	Autonomous robots 3D printing Augmented reality glass
Data processing	Big data and analytics Cyber-security
Connected logistics system	Automated inventory control Autonomous logistic system

Table 2-9. Sample Industry 4.0 Projects

Criteria	Sub-criteria	Author
Time	• Processing time • Prototyping time • Design revision time • experience time	Dulmin and Mininno (2003) Liao and Kao (2011) Asosheh et al (2010) Begicevic et al (2009)
Total cost and budget	• Hardware cost • Maintenance cost • Infrastructure cost • Consultant expenses • Labor cost • Cost of rework and scrap • Machinery cost	Lee and Kim (1999) Wei et al (2004) Kilic et al (2014) Haddara (2014) Efe (2016) Asl et al (2012) Erdogmus et al (2005)
Technical	• probability of technical success • existence of project champion • existence of required competence • availability of available resources • applicability to other products and processes • implementation ability • New technologies • Technological opportunity • Availability of skilled IT personnel • Technical capability	Meade and Presley (2002) Amiri (2010) Kilic et al (2014) Almeida et al (2013) Efe (2016) Haddara (2014) Pitic et al (2014) Wei et al (2004) Bolat et al (2018) Ma et al (2013)
Size and Market	• probability of market success of product • potential size of market • Product life cycle • Number and strength of competitors • Size and location	Meade and Presley (2002) Amiri (2010)
Human resources	• Planning • Training • Evaluation • Employee involvement • Human source requirements of system development • Ability to work in different business units	Marhraoui and Manouar (2017) Vinodh et al (2012) Yang et al (2011) Afshari et al (2010)
Quality	• Reduced process failures • Commitment	Liang and Li (2008) Nezhad (2017)
Potential risk	• Defects and returns	Ma et al (2013)

Table 2-10. Criteria for project selection for various industries.

2.6.2 Methods for project selection

Shahin and Mahbood (2007) implemented an integrated approach to prioritize the key performance indicators in terms of criteria of SMART (specific, measurable, attainable, and realistic, time sensitive) goal setting. They proposed an approach for prioritizing key performance indicators based on the integration of AHP and SMART. It involved following steps:

- Define and list all of the KPI's.
- Build AHP hierarchy based on SMART characteristics.
- Pair wise comparison
- Calculate global weight
- Select relevant KPI's

They conducted a case study considering five alternatives (KPI's) for a hotel. Using a nine-point scale, a comparison was made. They calculated the normalized pair wise values and found the reliability with the highest weight and rank 1. Following results were obtained:

Alternative	Global weight	Ranking
Responsiveness	5.1700	3
Tangibles	6.3768	2
Reliability	6.7575	1
Assurance	3.5760	4
Empathy	3.1196	5

Table 2-11. Results obtained from Shahin and Mahbod (2007)

External and internal effects which might affect the result are not considered. Also, the view of the people who are responsible for rating of the weights of KPIs might lead to an uncertain result. They have not considered different industries.

Daghouri et al (2018) evaluated the information system in construction industry sector based on the Delone and Mclean information systems success model. Five Moroccan organizations were ranked by TOPSIS method. The hierarchical model contains 6 criteria and 38 sub-criteria as they have grouped the different attribute into one category. They used AHP method to estimate the weights of the main criteria and sub-criteria. Data is collected with the help of an online questionnaire. Following table shows the 6 criteria and 38 sub-criteria:

Main criteria	Sub criteria
System Quality (C_1)	Availability(C_{11}), Employees Occupancy(C_{12}), Longest Delay(C_{13}), Answer Speed (C_{14}), Abandons(C_{15}), Blockage(C_{16}), Average hour of operation(C_{17}), Self-service and availability (C_{18})
Information quality (C_2)	Grammar and spelling(email) (C_{21}), Data accuracy(C_{22}), Secure(C_{23}), Complete(C_{24}), Relevant and correct(C_{25}), and Data Understand ability(C_{26})
Service quality(C_3)	On Time delivery(C_{31}), Knowledge and competency(C_{32}),Error Network(C_{33}), Availability(C_{34}), Access(C_{35}), Rate Delay(C_{36}) and Reliability (C_{37})
Use (C_4)	Frequency of use(C_{41}), Amount of use(C_{42}), Number of reports generated(C_{43}), Technical support(C_{44}), Managerial support(C_{45}) and Financial transactions use (C_{46})
User satisfaction(C_5)	Handle Time(C_{51}), Average Number of employees connected(C_{52}), Training Investment(C_{53}), Employee Turnover(C_{54}) and Average Satisfaction(C_{55})
Net benefits(C_6)	Return on investment(C_{61}), Productivity(C_{62}), Profit(C_{63}), Market Share(C_{64}), Growth in customer base(C_{65}) and Increased Sale (C_{66})

Table 2-12. Main criteria and sub-criteria (Source: Daghouri et al, 2018).

Schumacher et al (2016) describes the term maturity as a state of being complete, perfect, or ready and implies some progress in the development of a system. Accordingly, maturity systems increase their capabilities over time regarding the achievement of some desirable future state. Maturity can be captured qualitatively or quantitatively in a discrete or continuous manner. They introduced a three-step procedure to assess industry 4.0 maturity as follows:

- Step 1: Measurement of maturing items in enterprise via questionnaire (input).
- Step 2: Calculation of maturity level in nine dimensions software supported (output).
- Step 3: Representation and visualization of maturity via maturity report and radar charts.

A scale from 0 to 5 is used describing “not distinct” to “very distinct” respectively. E-mail based distribution of 123 questionnaires to practitioners and researchers resulted in 23 responses. They conducted a case study for an Austrian manufacturing industry who is already engaged in industry 4.0. The maturity level is calculated using the following formula:

$$M_D = \frac{\sum_{i=1}^{i=n} M_{Dli} * g_{Dli}}{\sum_{i=1}^{i=n} g_{Dli}} \tag{2.1}$$

M=maturity

D= dimension

I= item

G= weighting factor

n= number of maturity item

Yan and Chai (2017) used Analytic Hierarchy Process (AHP) and Fuzzy Comprehensive Evaluation method to evaluate the factors which influence the general aviation tourism industry of Xi’an. Their main objective of the research is to promote the development of general aviation tourism industry. They grouped the secondary indices to form the primary indices for their goal as follows. The AHP method was used to convert these evaluations to numerical values that were processed and compared over the entire range of the problem.

Hermann et al (2016) explained that Design principles explicitly address this issue by providing a “systemization of knowledge” and describing the constituents of a phenomenon. Therefore, design principles support practitioners in developing appropriate solutions. From an academic perspective, design principles are the foundation of design theory. They also illustrated a case study to identify the design principles in Industry 4.0. Using quantitative analysis and qualitative literature review following design principles for Industry 4.0 were obtained:

- Interconnection
- Information transparency
- Decentralized decisions
- Technical assistance

A case study was conducted to show how to utilize the four derived design principles. To evaluate the identified scenarios, a decision model using AHP is developed. A collaborative research project was initiated by a company from a chemical industry and the TU Dortmund University, Fraunhofer IML, and CDQ AG. Based on the results of evaluation, five scenarios were detailed out. Out of these, three scenarios were selected based on the discussion with the internal and external company experts. Han and Han in 2004, conducted a study for the selection of effective IC (intellectual capital) indicators. They proposed a decision model using Analytic Hierarchy Process. IC indicator selection was done by forming a hierarchy tree based on number of previous studies. The indicators were prioritized using the AHP method. Criteria weights were assigned by experienced managers and other experts. Such methods can be helpful in prioritizing the indicators for any industry.

Method	Author
AHP	Han and Han (2004) Wei et al (2004) Meade and Presley (2002) Hermann et al (2016)
AHP and Fuzzy TOPSIS	Efe (2016) Amiri (2010)
ANP and PROMETHEE	Kilic et al (2014)
Multi-attribute rating technique (SMART)	Shahin and Mahbood (2007) Haddara (2014)
Maturity model	Schumacher et al (2016)
Delphi and Shannon Entropy technique	Asl et al (2012)
PROMETHEE	Dulmin and Mininno (2003)
Fuzzy TOPSIS and Goal programming	Liao and Kao (2011)
Goal programming, Delphi and ANP methodology	Lee and Kim (1999)

Table2-13. Methods used for project selection.

2.7 Workforce selection

2.7.1 Criteria for workforce selection

The vision of industry 4.0 will bring not only new approaches but also the methodologies and technologies, which will have to be introduced into companies. The transition to such sophisticated production will not be possible immediately. It is expected that some professions will be replaced. Only qualified and highly educated employees will be able to control these technologies. In November 2017, the consulting firm Mckinsey highlights in its report that almost 800 million jobs are at risk due to implementation of new technologies, Trotta and Garengo (2018). The role of the human factor will be necessary for the future manufacturing. The skills and qualifications of the workforce will become the key to success of a highly innovative factory (Benesova et al., 2017). Bruecker et al (2015) presented that the planning of the workforce in a company is one of the most difficult problems managers face. As the size of the company increases, the problem tends to get more and more difficult. The workforce planning defines when and how many employees should be hired or dismissed and when these employees should work. Hence, it is a combination of staffing and scheduling decisions.

Workforce planning problems entail some special features that are absent in all other types of resource allocation problems. The basic point from where one can start the workforce planning is to determine the skills of the employees. Skills can be defined as the ability to perform certain tasks well. To analyze the importance of skills in workforce planning, skills can be divided into following:

Type of skill	Basic definition	Categories in industry 4.0
Hierarchical skills	In this type, workers with higher skill level can perform more than workers with lower skill level. Eventually, higher skilled workers can perform the tasks which are performed by the lower skilled workers as higher skilled workers are more educated and experienced than lower skilled workers. This is called substitution.	In industry 4.0, multi skill workers are preferred so that they can be utilized in every possible way. So, worker in the assembly section will have the knowledge of machines and can repair if by any chance some default occurs.
Categorical skills	In case of categorical skills, skills of one person are not better or worse than the skills of another person. There is no difference in skill level. Skills of a worker decide the task for that worker.	For example, in any manufacturing unit tasks associated with automation installment, robotic tasks or any other field associated task can be only done with the highly skilled person who is trained for that job.

Table 2-14. Types of skills (Source: Bruecker et al., 2015).

Complete system automation and use of advanced technologies, internet of things and big data analysis minimizes the human factor in the process but also it changes professionals inside the company as we know them today. One of the professions to be changed is the process planner. Longo et al (2017) described 5C architecture for industry 4.0. Based on that, we can discuss the new skills needed for the industry 4.0. Collaborating, this architecture with nine pillars of industry 4.0 we can describe the new skills needed for industry 4.0 as follows:

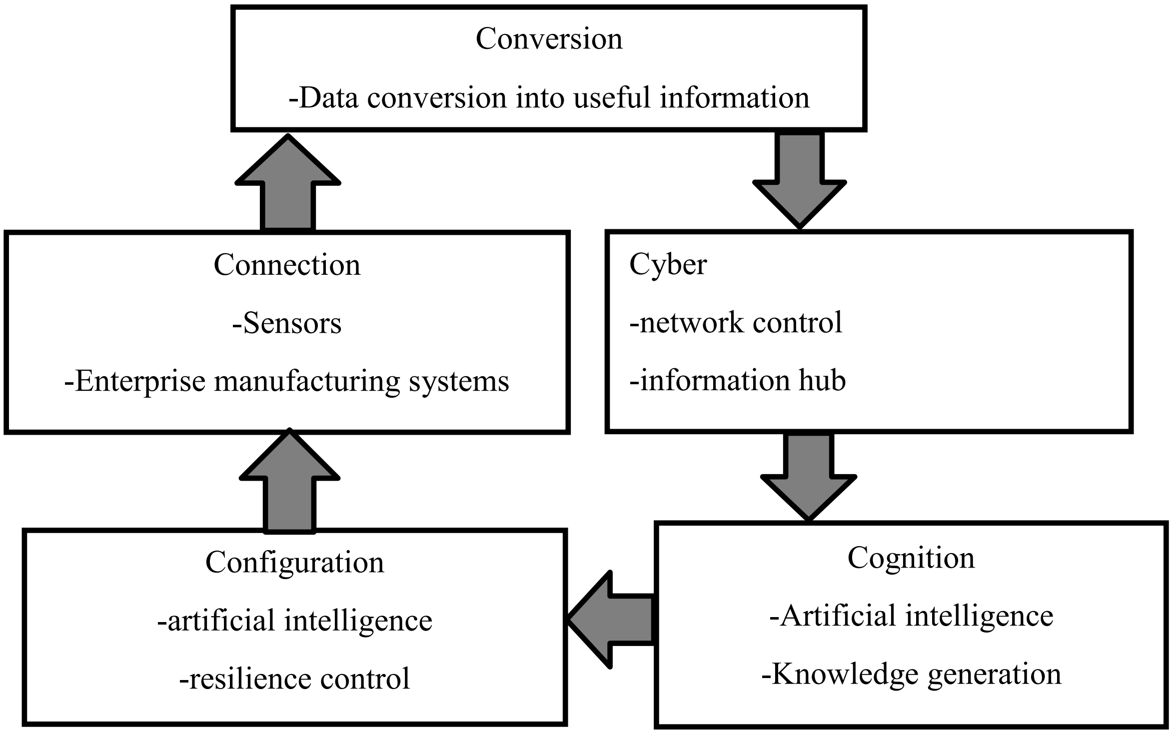


Figure 2-7. 5c Architecture for industry 4.0 (Source: Longo et al, 2017)

It is known that the development of new technologies tends to fail if workers start feeling that their job are threatened. The increased automation level also changes the shop floor landscape decreasing the low-skill work and increasing the high skill activities. So, the industries will be adopting continuous learning, training, and education of the workforce to adapt the qualification requirements resulting from industry 4.0 (Buer et al., 2018).

Technical implementation	**Skills needed**
ERP implementation	Process engineers for mapping of all processes.
Big data and data analytics	Engineers with basic knowledge statistically for problem solving. PL/SQL-advanced UML-advanced
Cloud system and services	Cloud system engineers and integrators to maintain and use stored and retained data. Knowledge of servers. Informatics specialist: knowledge of working with databases, virtualization and cloud services.
Data and cyber security	Engineers with analytical and logic thinking Knowledge of security standards and communication standards
Autonomous manufacturing	Robot programmer-with knowledge of off-line and on-line robot programming Installation of the device into operation PLC programmer-machinery programming and knowledge of PLC

Table 2-15. Skills needed for the 5c architecture of industry 4.0 (Source: Longo et al., 2017)

Karre et al (2017) described that as industry 4.0 enforces systems with a higher complexity due to automation and the interconnectivity of all its elements, organizational and processual understanding will be, among the other important skills, a basic qualification for industrial workers. These comprise the ability to recognize elements of the overall production system, identification of system borders, understanding of functions and relationships within the system and thereby to be able to predict the system behavior. With such an advancement in manufacturing sector dependency on one single worker can be detrimental. So, it is very important for the workers in industry 4.0 to have multi-skills to adopt the dynamic nature of industry 4.0. Thus, along with knowledge of their own core area, knowledge of other perspectives is very crucial to handle the complex system of industry 4.0. Following skills are structured into: “must have skills”, “should have skills” and “could have skills”.

Defined area of implementation	Must have skills	Should have skills	Could have skills
ERP implementation	• Process engineers for mapping of all processes.	• Awareness for IT-security and data protection	• Knowledge of manufacturing activities and processes
Big data and data analytics	• Engineers with basic knowledge statistically for problem solving. • PL/SQL-advanced • UML-advanced	• Interdisciplinary/generic knowledge about technologies and organization.	• Knowledge about statistical process control (SPC).
Cloud system and services	• Cloud system engineers and integrators to maintain and use stored and retained data. • Knowledge of servers. • Informatics specialist: knowledge of working with databases, virtualization and cloud services.	• Knowledge of big data and data security.	• Intelligent fabrication and social manufacturing.
Data and cyber security	• Engineers with analytical and logic thinking • Knowledge of security standards and communication standards	• Knowledge about computer coding and programming.	• Knowledge of cloud systems and services to integrate the data and services.
Autonomous manufacturing	• Robot programmer-with knowledge of off-line and on-line robot programming • Installation of the device into operation • PLC programmer-machinery programming	• Knowledge about maintenance of machines and robots • Knowledge about robot programming.	• Knowledge about manufacturing. • Basic knowledge of ERP system. • Knowledge of safety standards • Knowledge of technical documentation.

Table 2-16. Skills requirement for Industry 4.0 (Source: Karre et al, 2017)

Skills are worker's capability to complete assigned tasks to hit the organization targets. The difficulty of gaining specific skills and the capability of workers to catch up with skills and tasks determines the skill level variation. Besides, multiskilling is an effective methodology that enables workers to possess different type of skills and handle different tasks simultaneously. Cross-training is the approach used to equip workers with multi skills. Cross-training is an efficient approach to deal with workforce flexibility. Cross-training builds strong team work and enables workers to assist each other with secondary skilled task after completing their core job. Multi-skilled workers proficient in learning new technologies and switching job with different environment easily compared to single-skilled workers, Feng et al (2013). The author describes the different models for cross training as listed below.

Models	Explanation	Disadvantage
Skill chaining	Skill chaining produces chains of skills leading to a salient event where salience can be defined simply as an end of task reward, or as a more sophisticated heuristic. The goal of each skill in the chain is to reach a state where its successor skill can be executed. For example, the agent encounters the goal and creates a new sub goal, which later triggers the creation of a second skill to reach the first. Finally, after many trajectories the agent has created a chain of skills to reach the goal.	Challenging to implement this methodology to individuals as it requires pairs to be crossed trained.
Floating cross training strategy	In this strategy, each workstation is attended by a specialist (a worker who is not cross trained). Only one of the workers is cross trained. This worker can perform every task in the line. Floating worker represents a more experienced worker with a higher level of motivation and a higher wage level. For example, at Ford Motor co. such highly cross trained floating workers are often called "utility" workers.	Inefficient for long lines due to time consumption.
Fixed before shared principal	Under this strategy, cross trained workers can assist their peers with the shared tasks after completing their core tasks. In this case, cross trained workers need to be fast and efficient. This policy does not help the operation If the cross trained workers are slower than the specialized workers.	Solution from this study is limited to two to three worker systems and did not cover multifaceted systems.
Partial pooling strategy	Under this strategy, a small subset of super agents is cross trained. They are trained to increase the service level. It is more realistic than complete pooling.	Gets worst when the service time starts to fluctuate.
Partial cross training simulation based	Partial pooling implemented in manufacturing equipment maintenance environment with two types of technicians using hierarchical model.	Non-cross trained technicians contribute to shorter response time and increase emergency response time as they are not trained to handle emergency failures.

Table 2-17. Cross -training models (Source: Feng et al., 2013)

With the help of these models, we can conclude some benefits and drawbacks of cross training.

Benefits and drawbacks of cross training are as follows

Benefits of cross training	Drawbacks of cross training
➢ Cross training results in making workers more capable of handling many tasks at the same time, increasing their efficiency level. ➢ Worker's Productivity is increased. ➢ Multi skilled workers can cover absent peers to avoid overtime costs. ➢ Worker's idle and transition time is cut down. ➢ Labor cost is decreased. ➢ Workforce staffing and scheduling becomes easier due to the worker's flexibility. ➢ Substitution and cross training increase the flexibility of the workforce such that company can cope with the unexpected demand peaks without layoffs or hiring expensive new or temporary workers.	➢ It is very important to assign the right worker to the right task to reach certain level of quality. ➢ Significant cost is spent on instructors that train workers. ➢ When workers are asked to perform tasks other than their core tasks, their efficiency can decrease. ➢ Sometimes in cross training when higher skilled persons are required to perform the task which is designed for the lower skilled person downgrading occurs. ➢ Inefficiency in the operation occurs when workers are moved from one place to another. ➢ Learning-forgetting-relearning happens.

Table 2-18. Benefits and drawbacks of Cross-training models (Source: Feng et al., 2013)

Barlat in 2009 proposed that Workforce planning is an important process that enables organizations to determine the most Efficient workforce composition and provides a basis to recruit and/or reorganize the workforce to achieve organizational goals. A workforce plan is a framework for making staffing decisions based on an organization's mission, strategic plan, budget, and a set of required worker skills. An effective workforce plan has the right number of workers with the right skills in the right place at the right time. Unfortunately, simultaneously determining the *workforce allocation* - the number of workers with each skill set available during the planning horizon - and the *workforce utilization* - the sequence of tasks scheduled during the planning horizon to meet customer demand - is not a trivial task. Benesova et al (2017) stated that industry 4.0 will completely change the workforce strategies for many manufacturing industries. The emerging technologies will have huge effect on the education of people. Only highly qualified and highly educated employees will be able to control these technologies. The role of human factor will be very important for the future manufacturing. The skills and qualifications of the workforce will become the key to success of a highly innovative factory. For this reason, companies should focus on the qualified workforce by the human resource management. It not only includes selection, staffing and dismissing employees but also education, learning and training of employees. Educational qualifications will be higher than the present because companies will be implementing new technologies. Even though it is bringing the machine world up, but for the coming 10 years we need to have the human workforce but in a different direction. Implementation of industry 4.0 is not an abrupt procedure but it is a gradual process. Based on each phase of industry 4.0, different sections contain different kind of jobs, they described the following phases:

Phase	**Implementation**	**Job requirement**
Digital representation of factory in real time	Introduction of information system such as ERP	▪ Process engineers ▪ Specialists for cloud system and services.
Horizontal integration	New automated machines	▪ Process engineers will require a retaining course for the new automated machine.
Data analysis of vertical integration	Data processing	▪ Data analyst (knowledgeable in specified field) ▪ Data analyst (along with knowledge of the production process) ▪ Business data analyst
Self-controlling manufacture and logistic	Autonomous manufacturing	▪ Operators. ▪ Maintenance workers ▪ Data analysts ▪ Process engineers ▪ Quality controllers.

Table 2-19. Workforce requirements for different phases (Source: Benesova et al, 2017)

They described that the skills and qualifications of the workforce will become the key to success of a highly innovative factory. For this reason, the companies should focus on the development of qualified workforce by the human resource management. Requirements for the qualifications and skills of employees will be higher than at present, because the companies will use new technologies and smart media.

Kinzel (2016) explained that the designers of industry 4.0 concept appear to have a good grip on the technology of the system. However, the human factor seems not to be considered adequately. Humans are involved everywhere: as a team of system designers, a group of workers and our society as the clients of the manufactured goods. In the case of a complex system such as the Industry 4.0 concept, the entire society is at the "output" end of the automated manufacturing process. Systems do not (yet?) create themselves. There are teams of experts behind every new idea and very specialized engineers and software designers are required to convert the ideas into working software. Thus, even in industry 4.0, human factor plays a vital role.

In 2015, Lorenz et al revealed that there will be 6 percent increase in the employment but at the same time automation will displace the low skilled labourers and there will be increase in demand of employees in software development and IT technologies. These days company's productivity, profits and competitiveness greatly depends on how their employees are managed. Roux et al (2017) revealed that with the introduction of new technologies and new markets there will be introduction of new job categories with the use of human talent in a different direction. Hecklau et al (2016) published that with the introduction of new technology companies need to adopt new strategies for the holistic development of human resource management. They also proposed employee readiness level to conduct a competence gap analysis for required competencies in industry 4.0. Motyl et al (2017) conducted a research by organising 26 questions to investigate how the educational needs of students and of the industrial workforce are changing. They conducted the research to investigate which are the necessary skills and expertise young engineers require being ready for the industry 4.0 framework. They observed that the main important asset of the industry 4.0 framework is people. Workforce represents the critical aspect of the digital business transformation. Culture and education are the main keys for promoting knowledge and awareness about industry 4.0. Following table presents the criteria proposed by different authors.

Criteria	**Sub-criteria**	**Author**
Multi-skills for employees	• Ability to work in different business units • Strategic thinking • Computer skills • Core ability • General aptitude • Leadership • Culture protection and security of information	Afshari et al (2010) Gungor et al (2008) Dursun and Karsak (2010), Kabak (2012) Alguliyev et al (2015)
Technology evaluation and changes	Analysing the technological advancements needed	Ho and Frampton (2010)
Type of industry	• Manufacturing • Services • Others	Sanyal and Guvenli (2008)
Size and budget of the industry	• The importance of automating the process for the organization	De almeida et al (2013)
Time management	• Experience in management • Crisis management ability	Koutra et al (2017), Kundakci (2016)

Table 2-20. Criteria for workforce selection.

2.7.2 Methods for workforce selection

Many researchers in the past have purposed used different methods for the workforce selection and allocation. Gomar et al (2002) developed a model to optimize the workforce resource allocation and assignment process of a partially multi-skilled workforce. They developed the MOMA (multiskilling optimization model for allocation) model and their objective function was to minimize total number of workers, minimize switching and minimize hires and fires.

They concluded that assignment and allocation of a partially multi-skilled workforce can be optimized using this model. They also concluded that multi-skilled workers are always preferred by the optimization model over single skilled workers.

Multi-skill workers can survive easily in the era of industry 4.0 as compared to single skill workers. That is why, multi skill workforce selection and planning is comparatively hard. Wongwai and Malaikrisanachalee in 2011 used augmented heuristic algorithm for multi-skilled resource scheduling (AHAMRS). They compared the results with the existing heuristic approach concept. In AHAMRS, they assign available resource to the exact required resource to all current eligible activities in a priority order regardless of insufficient resources. Then, they examine the resource fulfilment in horizontal direction. They conducted the case study and observed that results with AHAMRS are far better than the existing heuristic approach. Same projects were covered in less numbers of days in AHAMRS.

Fowler et al (2007) used a MIP (Mixed Integer Programming) model based on the work of Wirojanagud et al (2007). Fowler and his colleagues tried to cover the gaps in their study. The objective of this paper is to develop simple and effective heuristics that reduce the computational time required to solve workforce planning problems of realistic size. They used linear programming to solve the rounding up and rounding down problem. The heuristic decides whether to round up or round down as rounding up creates overstaffing and rounding down creates missed production. The heuristic attempts to cross train the excess number of workers resulting from rounding up to cover the demand that is not fulfilled by rounding down. They also use genetic algorithm as a benchmark and also as an alternate which can be used for better results. Solution space partition (SSP) approach is used to reduce the problem size. They concluded that SSP and LP based heuristics provide feasible solution with a reasonable computational time.

Method	Author
Multiskilling optimization model for allocation (MOMA)	Gomar et al (2002)
Augmented heuristic algorithm for multi-skilled resource scheduling (AHAMRS)	Wongwai and Malaikrisanachalee (2011)
MIP (Mixed Integer Programming) model	Wirojanagud et al (2007)
ANP and TOPSIS	Dagdeviren (2008)
Fuzzy MULTIMOORA (Multi-objective optimization by ratio analysis)	Balezentis (2012)
Fuzzy MCDM	Dursun and Karsak (2010)
ANP and Fuzzy data envelopment analysis approach	Lin (2010)
Fuzzy DEMATEL (Decision making trial and evaluation laboratory)-ANP	Kabak (2011)
TOPSIS	Boran et al (2009)
TODIM method (Interactive and multi-criteria decision making)	Zhang and Wang (2016)
Modified Fuzzy VIKOR method	Algulivey et al (2015)
AHP	Koutra et al (2017)
Fuzzy-TOPSIS	Samanlioglu et al (2017)

Table 2-21. Method for workforce selection.

2.8 Limitation of existing works and research gaps

This section describes the research gap based on the previous researches in industry 4.0.

Author (Year)	Work Title	Advantages	Disadvantages
Lorenz et al (2015)	Industry 4.0: the future of productivity and growth in manufacturing industries.	Nine pillars were discussed thoroughly.	Nine pillars are not prioritized according to their importance
Schumacher et al (2016)	A maturity model for assessing industry 4.0 readiness and maturity of manufacturing enterprises	A multi-methodological development approach was carried out To evaluate the results, two case studies were conducted.	Standardized Questionnaires were developed only for one kind of industries
Flaviano celaschi. (2017)	Advanced design-driven approaches for an industry 4.0 framework: The human-centred dimension of the digital industrial revolution.	Description of primary and most common enabling technologies with their characteristics and applications.	No explanation for the methods required for the implementation of these technologies.
Carsten wittenberg (2016)	Human-CPS interaction-requirements and human-machine interaction methods for the industry 4.0.	Explained classical approach vs. digital factory approach	Didn't describe the risks associated with the tools used in digital factory approach.
Gorecky et al (2014)	Human-machine-interaction in the industry 4.0 Era.	Description of human responsibilities in usage of different cyber-physical system related technologies.	No description of training which is imperative for the labour due to the huge change in the technologies.
Chryssolouris et al (2009)	Digital manufacturing: History, perspectives, and outlook	Real examples for the implementation of applications associated with industry 4.0	The industries that benefit the most are those with capital-intensive manufacturing.
Leyh et al (2016)	SIMMI 4.0- A maturity model for classifying the enterprise-wide IT and software landscape focussing on industry 4.0.	Step by step approach to measure the level of digitization of any industry.	Real implementation is not provided.
Brettel et al (2014)	How virtualization, decentralization and network building change the manufacturing	Mass customization and collaborative manufacturing associated with CPS is explained.	Only large-scale industries can implement such strategies.

	landscape: an industry 4.0 perspective.		
Bley et al (2016)	Digitization of German enterprises in the production sector- do they know how digitized they are?	A real and actual implementation is done to find how digitized the industries are, based on implemented enterprise systems.	Other digital factors like manufacturing techniques, information sharing strategies were not considered.
Benesova et al (2017)	Requirements for education and qualification of people in industry 4.0.	Requirements for each phase and each job position are listed.	No technologies introduced for data security.
Motyl et al (2017)	How will change the future engineer's skills in the industry 4.0 framework? A questionnaire surveys.	Change in workforce is explained as per with the introduction of new technologies.	Technical strategies which need to be introduced for the change
Roux et al (2017)	Industry 4.0: preparing for the future of work.	Impact of industry 4.0 on future work and worker is discussed	No training or solution approaches are introduced for labours with low and conventional skills.
Hecklau et al (2016)	Holistic approach for human resource management in industry 4.0.	Digital skills and digital behaviour is measured by conducting a survey.	They did not consider business section as it was only for educational sector.

Table 2-22. Pros and cons of various literature.

It can be seen from above that there is currently no comprehensive framework that addresses the enterprise selection, project selection and workforce selection for Industry 4.0 altogether. This is the challenge we are addressing in this thesis.

Chapter 3:

Methodology

3.1 Introduction

In the previous chapter, using comprehensive literature review we have analysed the different possible problems faced by any industry for the implementation of industry 4.0. In this chapter, we will present the criteria and the solution approaches used to address the enterprise, project and workforce selection for Industry 4.0. Our methodology comprises of three inter-related components namely enterprise selection, project selection and workforce selection.

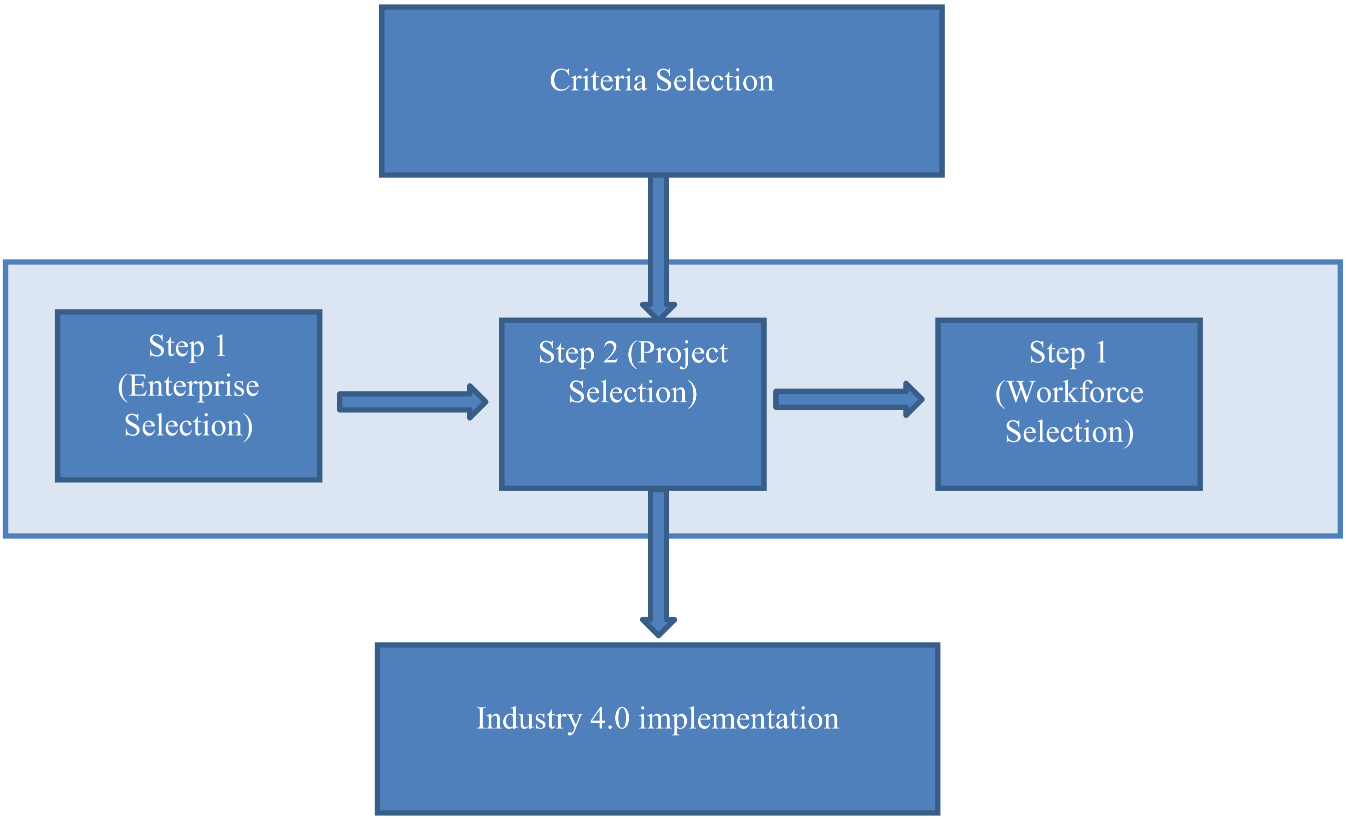


Figure 3-1: Digital enterprise planning

3.2 Criteria Selection for Industry 4.0

Three categories of criteria are proposed depending upon the problem being addressed namely Enterprise selection, Project selection, or Workforce selection. The Table below presents these criteria. The criteria were obtained by discussion with industry experts and literature studies.

Enterprise Selection	**Criteria Type**	**Authors**
Organization Type (manufacturing/service)	Benefit	Liao et al (2017), Gokalp et al (2016)
Organization Size (Large, Medium, SME)	Benefit	Chryssolouris et al (2009), Asl et al (2012)
Digital maturity level (state of IT implementation)	Benefit	Bley et al (2016), Tsai et al (2014)
Digital (IT) strategy	Benefit	Leyh et al (2016), samaranyake et al (2017)
Organization culture (international)	Benefit	Sarkis et al (2007)
Innovation	Benefit	Wan et al (2015)
Project Selection		
Implementation cost	Cost	Gunasekaran et al (2017)
Time to completion	Cost	Schumacher et al (2016)
Feasibility	Benefit	Brettel et al (2014)
Resource Requirements	Benefit	Fowler et al (2007)
IT Requirements	Cost	Lorenz et al (2015), Longo et al (20170
Expected Revenues	Cost	Thannimalai et al (2013)
Risk	Cost	Verdecho et al (2012)
Workforce Selection		
Computer skills (programming, human machine interface)	Benefit	Sampson (2006), Crispim et al (2009)
Soft skills (communication)	Benefit	Benesova and Tupa (2017)
Ability to work in different business units (multitasking)	Benefit	Askin and Huang (1997), Liao et al (2011)
Leadership	Benefit	Lin and Gen (2008), Vidic (2008)
Core skills (fundamentals, engineering)	Benefit	Walter and Zimmermann (2016), Sha and Che (2005)
Team thinking	Benefit	Balezentis et al (2012), Bhadury et al (2000)
General aptitude (problem solving)	Benefit	Algulivey et al (2015), Lill (2009)

Table 3-1. Proposed criteria for Industry 4.0 application

3.3. Prioritizing the Criteria

After determining the criteria for any industry, it is important to prioritize these indicators. There are various methods for prioritizing the indicators like AHP, TOPSIS, Fuzzy TOPSIS. The other potential method for prioritising criteria is AHP. It was developed by Saaty in 1980. It is a widely used decision-making method and can be applied to determine the weights of different criteria in a multi criteria decision-making (MCDM) problem. The weight elicitation process quantifies the subjective judgments of the expert and can evaluate the consistency of the collected opinions through the structured framework associated with the AHP (i.e., consistency ratio [CR]) Su et al (2014). In AHP, an identical matrix with indicators on rows and columns side is constructed. When two similar indicators are compared in the matrix, value will be zero. Each indicator is given a weight in the first column according to our priority. All other values will be constructed in the upper triangular region by dividing the values in column 1. It is very important to check the consistency because our assumption of assigning weight to indicators according to our priority can be wrong also. Steps for AHP can be described as follows:

Step 1: First, construct a set of pair-wise comparison matrices size n × n. for each of the lower levels with one matrix for each element in the level immediately above by using the relative scale measurement. The matrix obtained is the criteria comparison matrix.

$$C = \begin{array}{c} I_1 \\ I_2 \\ I_3 \\ I_4 \\ I_5 \\ I_6 \end{array} \begin{bmatrix} 1 & x_{12} & . & . & . & x_{1n} \\ x_{21} & 1 & . & . & . & x_{2n} \\ x_{31} & . & 1 & . & . & . \\ x_{41} & . & . & 1 & . & . \\ x_{51} & . & . & . & 1 & . \\ x_{61} & x_{62} & . & . & . & 1 \end{bmatrix} \tag{3.1}$$

About Saaty's pairwise comparison scale following values is used in the numerical method:

Scale	Definition	Explanation
1	Equal importance	Two elements contribute equally to the property
3	Moderate importance of one over another	Experience and judgement slightly favour one over the other
5	Essential or strong importance	Experience and judgement strongly favour one over another
7	Very strong importance	An element is strongly favoured, and its dominance is demonstrated in practice
9	Extreme importance	The evidence favouring one element over another is one of the highest possible order of affirmation
2,4,6,8	Intermediate values between two adjacent judgements	Comprise is needed between two judgements

Table 3-2. Saaty's Pairwise Comparison.

Step 2: This step is to obtain the normalized matrix. Normalized matrix can be obtained by dividing each column element by sum of the respective column. Sum of each column in a normalized matrix will be equal to 1.

Step 3: Calculate the criteria weights by taking the average of each row of the normalized matrix.

Step 4: The next step is to check the consistency of our result based on the assumptions we have made.

I. First, we need to obtain $\{w_s\}$ which can be obtained by the relationship *[c]**{w}. Here *[c]* is the criteria comparison matrix obtained in step 1 and *{w}* is the weighted matrix obtained in step 3.

II. Next step is to find consistency vector since we cannot divide a vector by a vector, so we will take a dot product here.

a. $$\{consistency\} = \{w_s\} * \{1/w\}$$ (3.2)

Ⅲ. In this step, calculate the consistency index using the formula below. Here, λ is the Eigen value which is calculated by taking the average of the matrix obtained in the above step.

$$CI = \frac{\lambda_{\max} - n}{n - 1}$$ *(n* is the matrix size) (3.3)

IV. The judgement consistency can be checked using the ratio CI/RI. Here, RI depends on the value of *n.*

The CR is acceptable, if it does not exceed 0.10. If it is more, the judgment matrix is inconsistent. To obtain a consistent matrix, judgments should be reviewed and improved. It will be clearer with the help of following flowchart:

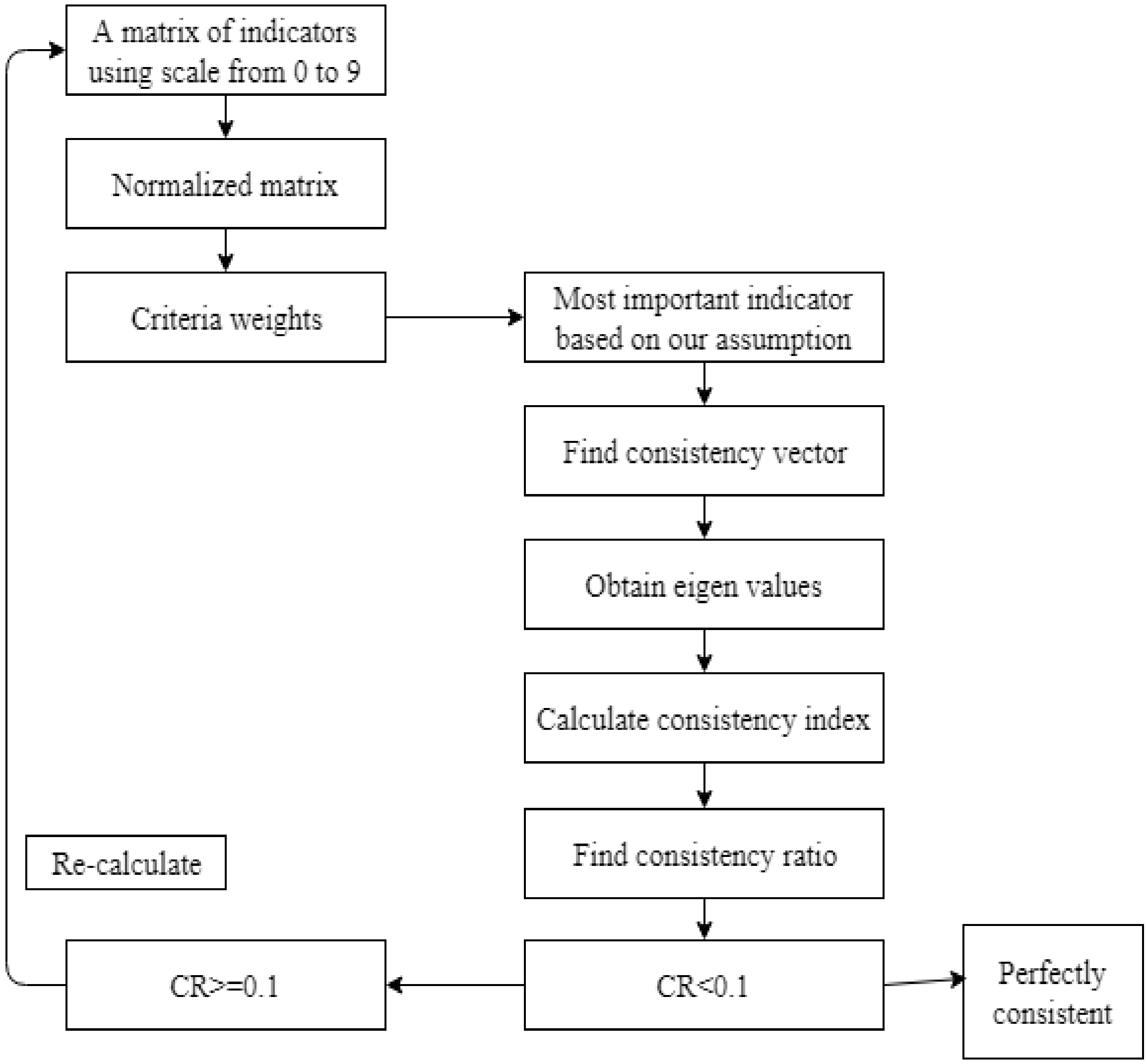


Figure 3-2. Description of AHP method.

But in our cases, we will be using TOPSIS method. For direct ranking, expert ratings were used. Experts rated the various criteria on a scale of 1-10, where 1 represents the lowest score and 10 represents the highest score. The aggregated scores were then normalized to determine criteria priorities (weights).

3.4 Evaluation Methods for Industry 4.0

Two methods were primarily used in our study for Industry 4.0 application namely TOPSIS (a multi-attribute decision making method) and Genetic Algorithms (meta-heuristic). These methods are described as follows:

3.4.1 MADM (Multi-attribute decision making)

Bohanec et al (1988) defined the decision-making problem as follows:

Given (aims or the goals of decision-maker)

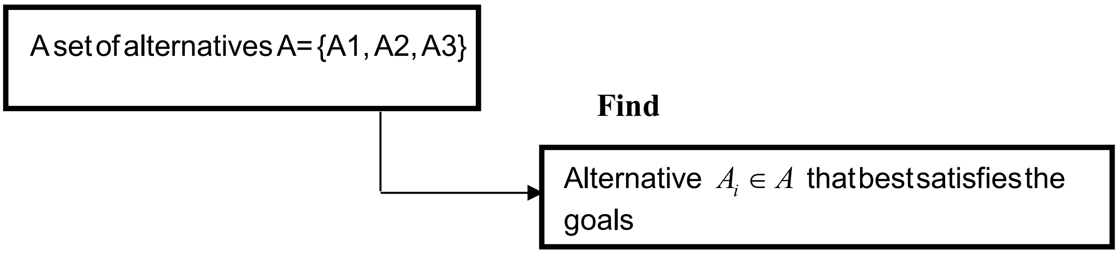


Figure 3-3. Definition of decision making problem.

The main role of decision methods and tools is to support decision makers in

• organizing and systematizing the facts, data and knowledge that influence the decision,

• Consistently applying these upon all alternatives, and in

• Further analysis and optimization of the alternatives.

Multi-attribute decision making methods can be combined with expert system technology to obtain a better quality in terms of decision knowledge acquisition and explanation, where an expert system plays the role of a cognitive support tool for decision making. The MADM methods belong to the general category of multi-criteria decision-making methods.

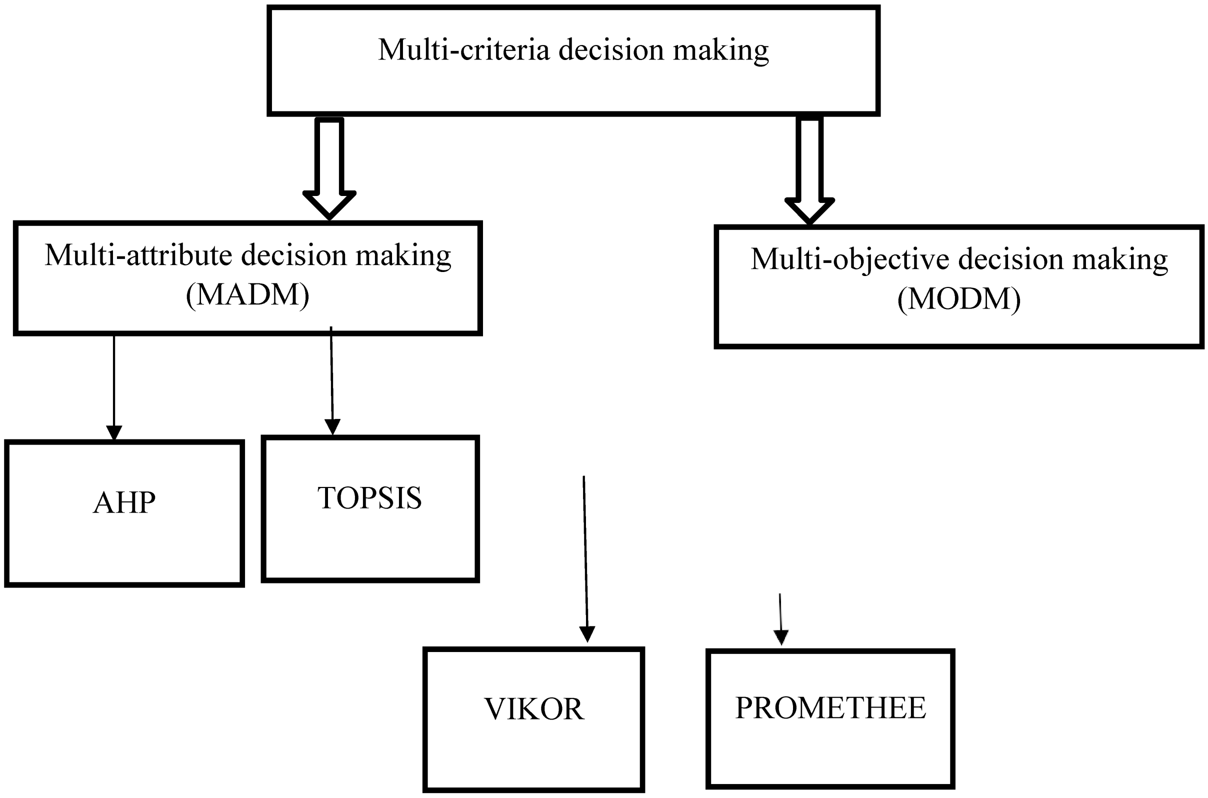


Figure 3-4. Multi-attribute decision making

Characteristics of multi-attribute decision making

- It considers the situation which involves several objectives or attributes or criteria. These are conflicting in nature and the process involves the selection of alternative which is predefined and finite number of alternatives is available for MADM problem.
- It involves the area in which criteria are measured in different units that is why the process which involves MADM process considers the normalization process because the units are defines in different scale and we need to normalize the whole given information and accordingly we can take the decision.
- In MADM methods we have the information about the attributes as well. For any decision-making problem we have 4 steps:

- Collection of information
- Quantification of information
- Modelling
- Action

We are using MADM instead of MODM due to following reason:

Characteristic	**MADM**	**MODM**
Criteria	Attribute	Objective
Objective	Implicit	Explicit
Attribute	Explicit	Implicit
Constraint math. Form	Inherent	Explicit
Alternative number	Finite number	Infinite number
Usage	Selection/evaluation	Design

Table 3-3. Difference between MADM and MODM.

Among the MADM methods, we will be using TOPSIS for application in the three problems. The strength of TOPSIS is that it is able to distinguish between positive and negative criteria and generates criteria ranking based on proximity to the ideal solution. More details on TOPSIS are provided as follows.

3.4.2 TOPSIS (Technique for order preference by similarity to ideal solution)

TOPSIS method is applicable for the process where we have different alternatives and according to the given criteria we can select which model is more suitable for us. It does not consider the pairwise information like AHP method. TOPSIS an MCDM method, was originally developed by Hwang and Yoon in 1981 with further development by Yoon in 1987, and Hwang, Lai and Liu in 1993 to identify solutions from a finite set of alternatives based upon simultaneous minimization of distance from an ideal point and maximization of distance from a nadir point. TOPSIS can incorporate relative weights of criterion importance. This Method assumes that we have m alternatives (options) and n attributes/criteria and we have the score of each option with respect to each criterion. Based on the mentioned principles, in this method, in addition to considering the distance of one alternative from the ideal point, its distance from the negative ideal point is also considered. It means that one elected alternative should be the shortest distance from the ideal solution and, at the same time, should be the greatest distance from the negative solution (Sadeghzadeh et al., 2011). TOPSIS basic concept is that the selected best solution from a finite set of alternatives should have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution in a geometrical sense. TOPSIS assumes that each attribute (or alternative) has a tendency toward monotonically increasing or decreasing utility. Therefore, it is easy to locate the (positive/negative) ideal solutions (Sepehr et al., 2012). Following flowchart describes the working of TOPSIS method:

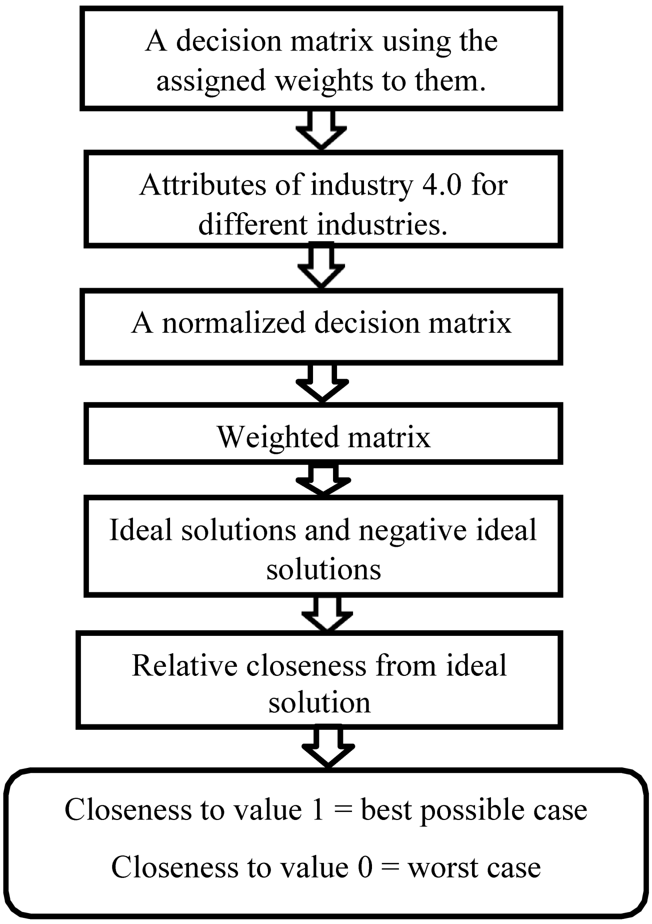


Figure 3-5. Description of TOPSIS method.

TOPSIS can be implemented through following steps:

Step 1: Establish a decision matrix of attributes of an industry according to their priority based on industry 4.0. The structure of matrix can be described as follows:

$$D = \begin{array}{c c} & \begin{array}{cccccc} C_1 & C_2 & . & . & . & C_n \end{array} \\ \begin{array}{c} I_1 \\ I_2 \\ . \\ . \\ . \\ I_m \end{array} & \begin{bmatrix} x_{11} & x_{12} & \cdot & \cdot & \cdot & x_{1n} \\ x_{21} & x_{22} & \cdot & \cdot & \cdot & x_{2n} \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ x_{m1} & \cdot & \cdot & \cdot & \cdot & x_{mn} \end{bmatrix} \end{array} \tag{3.4}$$

Where I_i denote industries considered to measure the readiness where i ranges from 1 to m. X_{ij} ($i = 1, \ldots, m$ and $j = 1, \ldots., n$) denote the attributes of industry 4.0 indicating the value of the attributes of respective industry assigned according to their priority.

Step 2: Next step is to calculate normalized decision matrix. As we know, different criteria have different units. So, data normalization is important to transform data to a specific range. There are various methods to normalize data like Min-max, standardization, Length-one or normalizing scaling, ordinal scale, normal scale, difference scale, absolute scale, linear normalization, non-monotonic normalization and vector normalization. We will be using the vector normalization method for normalization. The normalized matrix $R(=[\ r_{ij}\ ])$ can be calculated as:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^{\ 2}}} \tag{3.5}$$

Where $j = 1, \ldots., n$ and $I = 1, \ldots., m$.

Step 3: Calculate the weighted normalized decision matrix. It is simply the multiplication of normalized decision matrix by its associated weights. Thus, it is:

$$v_{ij} = w_{ij} \quad r_{ij} \tag{3.6}$$

Where w_{ij} represents the weight of the j_{th} attribute and r_{ij} is the normalized decision value.

Step 4: Determine the positive ideal solution (PIS) or negative ideal solution (NIS) respectively.

$$r^{+} = \{r_1^{+}, \ldots\ldots, r_n^{+}\} = \left(Max \quad r_{ij}; Min \quad r_{ij}\right) \tag{3.7}$$

$$r^{-} = \{r_1^{-}, \ldots\ldots, r_n^{-}\} = \left(Min \quad r_{ij}; Max \quad r_{ij}\right) \tag{3.8}$$

Step 5: Calculation of separation measure using the *m*-dimensional Euclidean distance. The separation from PIS can be calculated as:

$$s_i^{+} = \sqrt{\sum_{j=1}^{n} \left(r^{+} - r_{ij}\right)^2}, i = 1, 2, \ldots. m \tag{3.9}$$

Similarly, the separation from NIS can be calculated as:

$$s_i^{-} = \sqrt{\sum_{j=1}^{n} \left(r_{ij} - r^{-}\right)^2}, i = 1, 2, \ldots. m \tag{3.10}$$

Step 6: Calculate the relative closeness to the ideal solution. The relative closeness can be calculated as follows:

$$c_i = \frac{s_i^{-}}{s_i^{+} + s_i^{-}} \tag{3.11}$$

The index value of $_iC$ will lie between 0 and 1. The higher the value, the stronger is the recommendation to implement the industry 4.0 project based on the priorities assigned to the criteria. These results will be changed if we change the formula to the following:

$$c_i = \frac{s_i^{+}}{s_i^{+} + s_i^{-}}$$

The complete order obtained by the defined formula will be reversed. The best possible value will change to the worst possible if we change the designed formula.

3.4.3 Normalization Methods

In order to bring modelling parameters of different units to same scale, four normalization methods are used in our study. These methods are vector normalization, linear normalization (1), linear normalization (2), and linear normalization (3), and given as follows:

Normalization Methods	**Formula**
Vector Normalization	$r_{ij} = \frac{f_{ij}}{\sqrt{\sum_{j=1}^{n} f_{ij}^2}}$, $i=1,\ldots, m; j= 1,\ldots,n.$
Linear normalization (1)	$r_{ij} = \frac{x_{ij}}{x_j^*}$ $i=1,\ldots, m; j= 1,\ldots,n; x_j^*= \max_i\{x_{ij}\}$ benefit attributes $r_{ij} = 1 - \frac{x_{ij}}{x_j^*}, x_j^* = \max_i \{x_{ij}\}$ for cost attributes
Linear normalization (2)	$r_{ij} = \frac{x_{ij} - x_j^{\sim}}{x_j^* - x_j^{\sim}}, x_j^{\sim} = \min_i \{x_{ij}\}$ for benefit attributes $r_{ij} = \frac{x_j^* - x_{ij}}{x_j^* - x_j^{\sim}}$ for cost attributes
Linear normalization (3)	$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$ $i=1,\ldots, m; j= 1,\ldots,n.$

Table 3-4. Different normalization methods.

3.4.4 Genetic Algorithm

Genetic algorithms can be used to solve the optimization problem. Workforce planning can be utilized using Genetic algorithms. Genetic algorithms have many advantages over other conventional methods. It is more robust. Unlike older AI systems, GA's do not break easily even if the inputs changed slightly or in the presence of reasonable noise. While performing search in large-state space, multi-modal state space, or *n*-dimensional surface, a genetic algorithm offers significant benefits over many other typical search optimization techniques like linear programming, heuristic, depth first, breath-first, RC Chakraborty (2010).

GA's was developed by Holland and his colleagues in the 1960's. It is based on the theory of evolution. According to Smith et al (2006), GA are inspired by the evolutionist theory explaining the origin of species. In nature, weak and unfit species within their environment are faced with extinction by natural selection. The strong ones have greater opportunity to pass their genes to future generations via reproduction. In the long run, species carrying the correct combination in their genes become dominant in their population. Sometimes, during the slow process of evolution, random changes may occur in genes. If these changes provide additional advantages in the challenge for survival, new species evolve from the old ones. Unsuccessful changes are eliminated by natural selection. Important terms of genetic algorithm are:

Population pool: Set of possible solutions. The population is randomly initialized.

An objective function: which is to be minimized or maximized.

Fitness function: used to find the fittest parents to produce fittest off-springs.

Cross-over: it is the most important operator which is used to combine the fittest parents to produce the off-springs.

Mutation: The mutation operator introduces random changes into characteristics of chromosomes. Mutation is generally applied at the gene level. In typical GA implementations, the mutation rate (probability of changing the properties of a gene) is very small and depends on the length of the chromosome. Therefore, the new chromosome produced by mutation will not be very different from the original one. Mutation plays a critical role in GA. As discussed earlier, crossover leads the population to converge by making the chromosomes in the population alike. Mutation reintroduces genetic diversity back into the population and assists the search escape from local optima, Smith et al (2006). Following steps can be followed to find the optimal solution:

- Step 1: Generate a random pool of population P1 of N solutions.
- Step 2: Evaluate the fitness function of solutions in P1.
- Step 3: Choose two fittest values x and y from P1. Generate off-springs by using a cross-over operator. Offspring population can be termed as Q1.
- Step 4: Randomly mutate any solution in Q1 matrix with a pre-defined mutation rate.
- Step 5: Calculate the fitness function for each solution in Q1 matrix.
- Step 6: Based on the fitness value according to our pre-defined condition, add the solutions (Fittest) from Q1 to P1.
- Step 7: If our pre-defined condition is satisfied, terminate the search or go to step 3 to create other Q2 matrix. Following flowchart describes the working of Genetic algorithm:

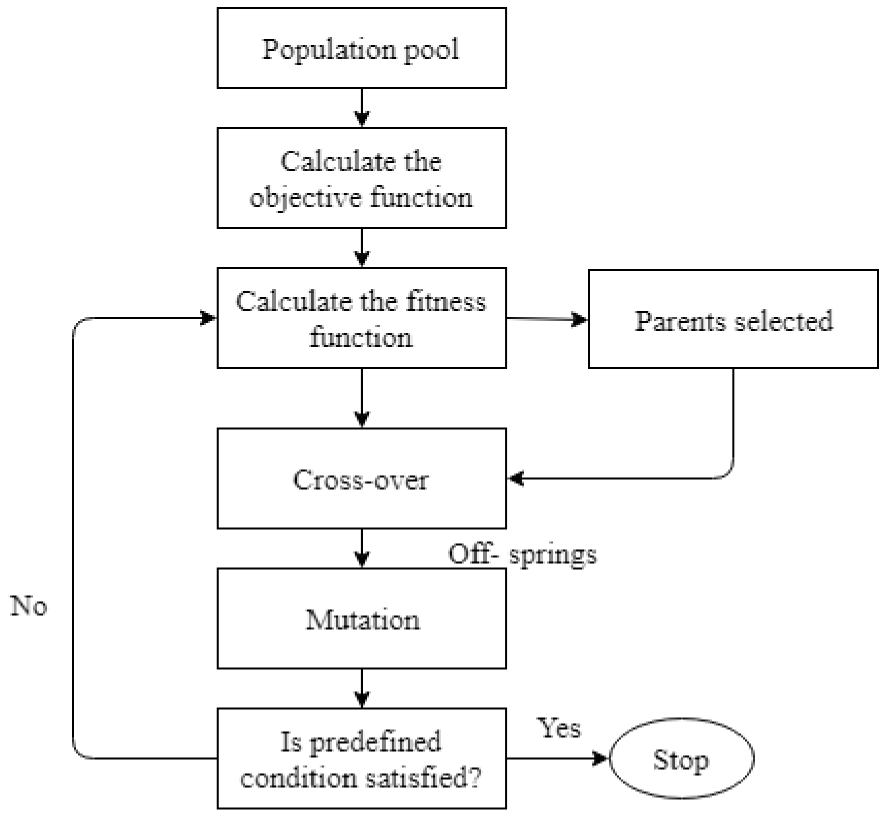


Figure 3-6. Genetic algorithm steps.

The genetic algorithms offer a wide range of solutions to optimization problems. The genetic algorithms are a class of stochastic relaxation techniques that are applicable to the solution of a wide variety of optimization problems, by emanating the evolutionary behavior of biological systems, Reid et al (1996). Decision making associated with workforce planning results in difficult optimization problems because it involves multiple levels of complexity, Enrique Alba et al. In industry 4.0, workforce planning is an important issue especially when workers are cross-trained for multi-skills. It is important to know which workers can perform the task and how many hours they need to perform the task. Optimization techniques are useful when our main goal is to maximize the profit and minimize the cost. The basic feature of genetic algorithms is the multiple directional and global searches, in which a population of potential solutions is maintained from generation to generation. A useful feature of genetic algorithm is to handle multi-objective function optimization, Lin and Gen (2008). To efficiently utilize the benefits of cross-training, it is very important to implement workforce planning and human resource allocation in an efficient way. Following steps can be followed to solve an optimization problem using genetic algorithm:

3.4.5 Method for workforce selection

Let us consider an industry that wants to perform a task in a day which includes two jobs, with certain number of workers. They have a budget to perform the task. The industry wants to know the number of hours they should assign to each worker so that they can perform the task keeping the cost as minimum as possible. They have four categories of workers to perform job 1 and job 2 of the task. It can be described as,

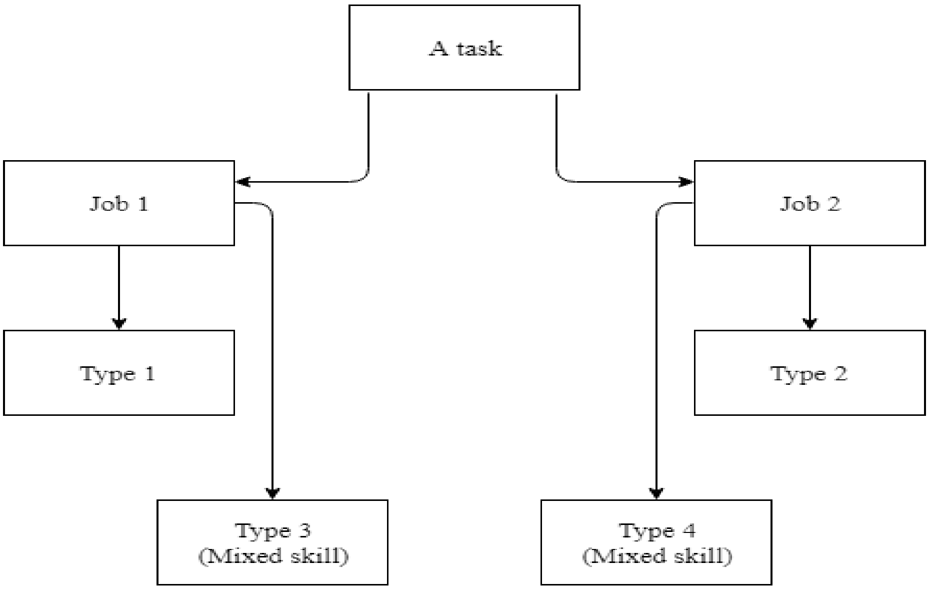


Figure 3-7. Problem representation of GA.

Type 1: x_i workers who can perform job 1.

Type 2: y_i workers who can perform job 2.

Type 3: z_i' is the number of hours for workers from mixed skill category who can perform job 1.

Type 4: z_i'' is the number of hours for workers from mixed skill categories who can perform job 2.

w_i: Wages for each category of workers.

So, our objective function is the cost minimization but keeping in mind the possible constraints setup by the industry. So,

Objective function

$$\text{Min} f(x) = \sum_{i \in type1} w_i x_i + \sum_{i \in type2} w_i y_i + \sum_{i \in type3} w_i z_i' + \sum_{i \in type4} w_i z_i'' \quad (3.12)$$

Here, *f(x)* is the total cost.

Constraints:

$\sum_{i \in type1} w_i x_i + \sum_{i \in type2} w_i y_i + \sum_{i \in type3} w_i z_i' + \sum_{i \in type4} w_i z_i'' \le D$ Here, D is the per day budget for the tasks.

$z_i' + z_i'' \le q$ Here, q is the upper limit of hours for mixed skill workers.

$x_i, y_i, z_i', z_i'' \in [u, v]$ Here, u and v is the lower and upper limit of hours compulsory for each worker, respectively.

Step 1: Select a pool of possible solutions from your own priorities and estimation. The population pool matrix be:

$$\begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{14} \\ x_{21} & . & . & x_{24} \\ x_{31} & . & . & . \\ x_{41} & . & . & x_{44} \end{bmatrix} \tag{3.13}$$

Step 2: Calculate the objective function using the values from the population pool for number of hours and the value of fixed wages is provided by the industry.

Step 3: Calculate the fitness function using the rank-based method. We will be using Rank based technique for the selection of parents. The rank can be assigned to them using the following equation:

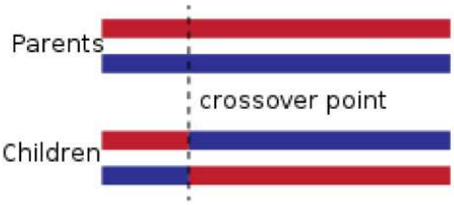
$Rank_1 < Rank_2$ If

$$abs(optimal - work)_1 < abs(optimal - work)_2 \tag{3.14}$$

Here, optimal solution is the per day budget of the industry.

Step 4: The next step is to cross-over the fittest parents to produce the fittest off-springs. Crossover is a recombined operator for two high-fitness strings (parents) to produce two offspring by matching their desirable qualities through a random process, Ketabchi et al (2013).

We adopted a single point cross-over method. A single crossover point on both parents' organism strings is selected. All data beyond that point in either organism string is swapped between the two parent organisms. The point of cross over is selected randomly. The resulting organisms are the children:



Step 5: In this step, mutation is performed. It is simply the replacement of the value in the mutated matrix with a random value. Mutation plays the role of safeguard in genetic algorithm.

Step 6: Calculate the fitness function for the matrix obtained in step 5. Perform these steps for much iteration to get the fittest solution as per our constraints.

Chapter 4

Numerical Application

4. 1 Enterprise selection

In the previous chapter, we presented our solutions for the problems described in chapter 2. In this section, we will demonstrate their application using real data sets and case study.

4.1.1 Criteria for Enterprise selection

We are using TOPSIS method to select the enterprise for the implementation of industry 4.0 project. Let us assume there are 4 manufacturing I_1, I_2, I_3, I_4 industries who want to implement industry 4.0 project. They already are at full digitization stage. Thus, we are implementing advanced level of digitization in an industry. We will consider the following six criteria for industry 4.0. Following indicators are realized with the help of the indicators realized in *table 2-1* for advanced level implementation of the industry 4.0.

C_1= Organization Type (manufacturing/service)

C_2= Organization Size (Large, Medium, SME)

C_3= Digital maturity level (state of IT implementation)

C_4= Digital (IT) strategy

C_5= Organization culture (international)

C_6= Innovation

4.1.2 Method for Enterprise selection

Step 1: A scale from 1 to 10 is used to assign them the weights according to their priorities. Higher the rank, higher is the priority. Following decision matrix is obtained which can be named as Q matrix. Here, attributes are taken horizontally, and industries are represented vertically. These values are based on the survey conducted.

$$\begin{array}{c} \\ I_1 \\ I_2 \\ I_3 \\ I_4 \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \end{array} \\ \begin{pmatrix} 8 & 7 & 9 & 9 & 7 & 10 \\ 3 & 7 & 9 & 10 & 5 & 8 \\ 7 & 8 & 8 & 8 & 6 & 6 \\ 10 & 10 & 9 & 10 & 5 & 7 \end{pmatrix} \end{array} \tag{4.1}$$

Step 2: In this step, we will normalize the decision matrix obtained in the step 1. Normalization is really an important to make the same base because attributes can have different units when we are considering different industries. Our normalization matrix is:

	C1	C2	C3	C4	C5	C6
I1	0.536925	0.432461	0.513657	0.484544	0.602464	0.633724
I2	0.201347	0.432461	0.513657	0.538382	0.430331	0.506979
I3	0.469809	0.494242	0.456584	0.430706	0.516398	0.380235
I4	0.671156	0.617802	0.513657	0.538382	0.430331	0.443607

(4.2)

Step 3: We will develop a set of importance weights w_k for each of the column. These weights can be random numbers but usually they are ad hoc reflective of relative importance. Following weights are calculated

$$
\begin{aligned}
W_1 &= 0.14 \\
W_2 &= 0.17 \\
W_3 &= 0.19 \\
W_4 &= 0.20 \\
W_5 &= 0.12 \\
W_6 &= 0.16
\end{aligned}
\tag{4.3}
$$

Step 3: Weighted decision matrix named v_{ij}, obtained my multiplying each weight with the respective column. Here, columns are the weights assigned to the criteria by different expertise. These weights are obtained with the help of a survey conducted. So, our weighted decision matrix obtained is as follows:

V_{ij}=

	C1	C2	C3	C4	C5	C6
I1	0.075169	0.073518	0.097595	0.096909	0.072296	0.101396
I2	0.028189	0.073518	0.097595	0.107676	0.05164	0.081117
I3	0.065773	0.084021	0.086751	0.086141	0.061968	0.060838
I4	0.093962	0.105026	0.097595	0.107676	0.05164	0.070977

(4.4)

Step 4: Positive ideal solutions (PIS) and negative ideal solutions (NIS) are as follows:

V+	0.093962	0.105026	0.097595	0.107676	0.072296	0.101396

(4.5)

V-	0.028189	0.073518	0.086751	0.086141	0.05164	0.060838

(4.6)

Step 5: The separation from PIS (S_i^+) and NIS (S_i^-) can be calculated as:

Si+	Si-
0.038234	0.067174
0.078465	0.031506
0.05974	0.040368
0.036769	0.077479

Step 6: Relative closeness to ideal solution can be calculated as:

$I_1 = 0.63$ $\qquad\qquad$ $I_2 = 0.28$

$I_3 = 0.40$ $\qquad\qquad$ $I_4 = 0.67$

As we know, relative close to value 1 is the best possible case and closeness to value 0 is the worst possible case. So, according to the priorities assigned to the attributes, industry I_4 is highly capable of implementing industry 4.0. Following table describes the ranking with different normalization methods.

Normalization Methods	**Ranking results**
Vector Normalization	$I_4>I_1>I_3>I_2$
Linear normalization (1)	$I_4>I_1>I_3>I_2$
Linear normalization (2)	$I_4>I_1>I_2>I_3$
Linear normalization (3)	$I_4>I_1>I_3>I_2$

Table 4-1. Impact of normalization on ranking results

4.2 Project selection

4.2.1 Criteria for project selection

After the selection of industry, our next step is to prioritize the indicators. There are different attributes for industry 4.0. But it is very important to know which indicator to implement first. It is not possible to implement all the indictors at once as it needs a huge budget. Moreover, industries are reluctant to implement all the indicators as they are not sure about the results. Here, we will use the TOPSIS method to prioritize the indicators. So, higher important indicators can be implemented first. We already discussed this method in the previous chapter. Now, we will consider a numerical example for the practical usage. Following are our criteria for the project selection which are obtained using the results of survey conducted.

C_1=Implementation cost

C_2= Time to completion

C_3= Feasibility

C_4=Resource Requirements

C_5= IT Requirements

C_6= Expected Revenues

C_7 = Risk

4.2.2 Method for project selection

As before, we will use the TOPSIS method by following steps. In TOPSIS method, we will consider the same criteria. We have discussed the steps for TOPSIS earlier. So, here we will just implement the result.

Step 1: Our decision Matrix say D, based on the Survey conducted is as follows

$$D = \begin{array}{c} \\ P_1 \\ P_2 \\ P_3 \\ P_4 \end{array} \begin{array}{c} \begin{array}{ccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 \end{array} \\ \begin{pmatrix} 7 & 10 & 10 & 9 & 9 & 9 & 9 \\ 8 & 5 & 7 & 4 & 10 & 6 & 9 \\ 9 & 7 & 5 & 6 & 6 & 8 & 6 \\ 9 & 10 & 7 & 10 & 9 & 9 & 5 \end{pmatrix} \end{array} \quad (4.7)$$

Step 2: Our normalized matrix R is as follows:

	C1	C2	C3	C4	C5	C6	C7
P1	0.422116	0.604122	0.66965	0.58961	0.521356	0.556022	0.602685
P2	0.482418	0.302061	0.468755	0.262049	0.579284	0.370681	0.602685
P3	0.54272	0.422885	0.334825	0.393073	0.347571	0.494242	0.40179
P4	0.54272	0.604122	0.468755	0.655122	0.521356	0.556022	0.334825

(4.8)

Step 3: Our weighted matrix is as follows:

$W_1 = 0.17$
$W_2 = 0.14$
$W_3 = 0.13$
$W_4 = 0.13$
$W_5 = 0.16$
$W_6 = 0.14$
$W_7 = 0.13$

Step 4: Weighted decision matrix can be calculated as:

	C1	C2	C3	C4	C5	C6	C7
P1	0.059096	0.102701	0.127233	0.117922	0.062563	0.088963	0.078349
P2	0.067539	0.05135	0.089063	0.05241	0.069514	0.059309	0.078349
P3	0.075981	0.071891	0.063617	0.078615	0.041708	0.079079	0.052233
P4	0.075981	0.102701	0.089063	0.131024	0.062563	0.088963	0.043527

(4.9)

Step 4: Positive ideal solutions (PIS) and negative ideal solutions (NIS) are as follows:

V+	0.059096	0.05135	0.127233	0.05241	0.041708	0.088963	0.043527

(4.10)

V-	0.075981	0.102701	0.063617	0.131024	0.069514	0.059309	0.078349

(4.11)

Step 5: The separation from PIS (S_i^+) and NIS (S_i^-) can be calculated as:

Si+	Si-
0.19397	0.18495
0.066282	0.097652
0.074928	0.074445
0.104853	0.0528

Step 6: Relative closeness to ideal solution can be calculated as:

$P_1 = 0.48$ $\qquad$ $P_2 = 0.59$

$P_3 = 0.49$ $\qquad$ $P_4 = 0.33$

As we know closeness to value 1 provides the best solution. Thus, industry I_4 which was selected in Enterprise selection method, can implement project 2 first. To evaluate we have checked the impact of different normalization methods on the ranking. Since cost and benefit attributes are involved so results differ depending upon the formulae used.

Normalization Methods	**Ranking results**
Vector Normalization	$P_2 > P_3 > P_1 > P_4$
Linear normalization (1)	$P_1 > P_4 > P_2 > P_3$
Linear normalization (2)	$P_4 > P_2 > P_1 > P_3$
Linear normalization (3)	$P_3 > P_2 > P_1 > P_4$

Table 4-2. Impact of normalization on ranking results

4.3 Workforce selection

4.3.1 Criteria for workforce selection

As discussed previously, the industry wants to perform the task which includes two jobs. They have above mentioned four categories of workers which can do this task. Type 3 and type 4 are the mixed skill workers so they are more expensive. The company has a per day budget of 1000$ for this task. A worker can work between 1 to 8 hours in a day. The company wants to know the number of hours they should assign to each worker keeping the cost under-budget. Since company must pay more to type 3 and type 4, the number of hours for these categories should not be more than 15. All workers must work at least 1 hour a day. The mutation rate is 10%.

So, the objective function of this problem is the minimization of the cost which can be described as:

$$f(x)=\sum_{i\in type1} w_i x_i+\sum_{i\in type2} w_i y_i+\sum_{i\in type3} w_i z_i'+\sum_{i\in type4} w_i z_i'' \tag{4.12}$$

w_i For type 1 = 40$/hour

w_i For type 2 = 45$/hour

w_i For type 3= 50$/hour

w_i For type 4= 55$/hour.

Constraints for our case study are:

$$\sum_{i\in type1} w_i x_i+\sum_{i\in type2} w_i y_i+\sum_{i\in type3} w_i z_i'+\sum_{i\in type4} w_i z_i'' \le 1000$$

$$z_i^{'}+z_i^{''}\le 15 \tag{4.13}$$

$$x_i, y_i, z'_i, z''_i \in [1,8] \tag{4.14}$$

Step 1: Set up the population pool of random solutions with population size 16. We will take a matrix of 4×4. Matrix P is generated keeping the constraints in mind.35)

$$\begin{array}{c} P_1 \\ P_2 \\ P_3 \\ P_4 \end{array} \begin{pmatrix} 8 & 1 & 2 & 4 \\ 4 & 1 & 2 & 2 \\ 7 & 5 & 8 & 2 \\ 6 & 8 & 3 & 7 \end{pmatrix} \tag{4.15}$$

For the first iteration, we will not calculate the objective function and fitness function to find the fittest parents for cross-over because it is a randomly generated pool. So, we will do the cross-over randomly.

Step 2: So, we will randomly cross-over the elements in matrix P. we will use single cross-over point. We will do the cross-over on second element of each row. Elements obtained after cross-over are:

$$\begin{array}{c} P_1P_2 \\ P_2P_4 \\ P_3P_1 \\ P_4P_2 \end{array} \begin{pmatrix} 8 & 1 & 2 & 2 \\ 4 & 1 & 3 & 7 \\ 7 & 5 & 2 & 4 \\ 6 & 8 & 2 & 2 \end{pmatrix} \tag{4.16}$$

Step 3: Mutation is the simple replacement of the value in the cross-over matrix with any random value. Our mutation rate is 10%. So, in the matrix of 16 elements there will be chance of only one value mutated. Matrix obtained after mutation is:

$$\begin{array}{c} Q_1 \\ Q_2 \\ Q_3 \\ Q_4 \end{array} \begin{pmatrix} 4 & 1 & 2 & 2 \\ 4 & 1 & 3 & 7 \\ 7 & 5 & 2 & 4 \\ 6 & 8 & 2 & 2 \end{pmatrix} \tag{4.17}$$

Now, we have obtained a pool of population. So, calculate the objective function of this population pool. In short, we will repeat the steps to find the optimal solution.

Step 1: Objective function can be calculated as

	$f(Q_1)$	$f(Q_2)$	$f(Q_3)$	$f(Q_4)$
Values	415	740	825	810

Step 2: Calculate the fitness function using the rank-based method to find the fittest parents to produce fittest off-spring. The equation is

$Rank_1 < Rank_2$ if

$$abs(optimal - work)_1 < abs(optimal - work)_2 \tag{4.18}$$

Here, optimal value is the per day budget of the industry. And work is the value of objective function obtained with the values of Q matrix. So, fitness function and respective rank is as follows:

	Q_1	Q_2	Q_3	Q_4
Values	585	260	175	190
Rank	4	3	1	2

These parents can be arranged in an ascending order according to their fitness level as follows:

$$Q_3 > Q_4 > Q_2 > Q_1 \tag{4.19}$$

Step 3: Based on the fitness, cross-over the fittest parents to produce the fittest off-springs. In our numerical solution we are using single point cross over on the second element of the row. Cross-over can be displayed as:

$$\begin{array}{c} Q_3Q_2 \\ Q_3Q_4 \\ Q_4Q_2 \\ Q_4Q_1 \end{array} \begin{pmatrix} 7 & 5 & 3 & 7 \\ 7 & 5 & 2 & 2 \\ 6 & 8 & 3 & 7 \\ 6 & 8 & 2 & 2 \end{pmatrix} \tag{4.20}$$

Step 4: Now, mutate any value with random value between 4 to 8. The mutated matrix M is obtained as:

$$M = \begin{bmatrix} 7 & 5 & 3 & 7 \\ 7 & 5 & 2 & 2 \\ 6 & 8 & 3 & 7 \\ 6 & 4 & 2 & 2 \end{bmatrix} \tag{4.21}$$

Step 5: Next, calculate the objective function for M matrix. It can be stated as:

	M_1	M_2	M_3	M_4
Values for objective function	1040	715	1135	630
Fitness function using the equation	40	285	135	330

So, their fitness can be explained as:

$$M_1 > M_3 > M_2 > M_4 \tag{4.22}$$

Application results

Since M_1 has the minimum difference between the optimal solution and solution obtained. Industry can accept this decision or can go for many other iterations until the difference between the optimal and the obtained decision becomes zero or less than the value obtained in the previous iteration value. So, if company gives following hours to the worker, they can achieve the target within their budget and considering the constraints.

Type	$Type_1$	$Type_2$	$Type_3$	$Type_4$
Hours	7 hours	5 hours	3 hours	7 hours

4.3.2 TOPSIS for workforce selection

For workforce selection we will be using the TOPSIS method again. As per the survey conducted for the criteria following decision matrix is obtained based on the responses observed from different expertise.

Step 1: Here, WF_1, WF_2, WF_3 and WF_4 represent different industries which participated in the survey. C_1, C_2, C_3, C_4, C_5, C_6 and C_7 are different criteria for workforce selection where

$C_{1=}$ Computer skills (programming, human machine interface)

$C_{2=}$Soft skills (communication)

$C_{3=}$ Ability to work in different business units (multitasking)

$C_{4=}$ Leadership

$C_{5=}$Core skills (fundamentals, engineering)

$C_{6=}$ Team thinking

$C_{7=}$ General aptitude (problem solving)

$$\begin{array}{c} \\ WF_1 \\ WF_2 \\ WF_3 \\ WF_4 \end{array} \begin{array}{c} \begin{array}{ccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 \end{array} \\ \begin{pmatrix} 10 & 8 & 8 & 7 & 9 & 9 & 9 \\ 9 & 5 & 6 & 8 & 10 & 7 & 4 \\ 6 & 5 & 5 & 4 & 4 & 4 & 4 \\ 7 & 7 & 9 & 9 & 9 & 6 & 6 \end{pmatrix} \end{array}$$

Step 2: Normalized Matrix R is as follows:

	C1	C2	C3	C4	C5	C6	C7
WF1	0.613139	0.626608	0.557386	0.483046	0.539784	0.667124	0.737309
WF2	0.551825	0.39163	0.41804	0.552052	0.59976	0.518875	0.327693
WF3	0.367884	0.39163	0.348367	0.276026	0.239904	0.2965	0.327693
WF4	0.429198	0.548282	0.62706	0.621059	0.539784	0.44475	0.491539

Step 3: Our weighted matrix is

$W_1 = 0.16$
$W_2 = 0.12$
$W_3 = 0.14$
$W_4 = 0.14$
$W_5 = 0.16$
$W_6 = 0.13$
$W_7 = 0.11$

Step 4: Weighted decision matrix named v_{ij}, obtained my multiplying each weight with the respective column is given as follows:

	C1	C2	C3	C4	C5	C6	C7
WF 1	0.098102	0.075193	0.078034	0.067626	0.086365	0.086726	0.081104
WF 2	0.088292	0.046996	0.058526	0.077287	0.095962	0.067454	0.036046
WF 3	0.058861	0.046996	0.048771	0.038644	0.038385	0.038545	0.036046
WF 4	0.068672	0.065794	0.087788	0.086948	0.086365	0.057817	0.054069

(4.23)

Step 5: Positive ideal solutions (PIS) and negative ideal solutions (NIS) are as follows:

V+	0.098102	0.075193	0.087788	0.086948	0.095962	0.086726	0.081104

(4.24)

V-	0.058861	0.046996	0.048771	0.038644	0.038385	0.038545	0.036046

(4.25)

Step 6: The separation from PIS (S_i^+) and NIS (S_i^-) can be calculated as:

Si+	Si-
0.000561	0.237792
0.065135	0.081274
0.117717	0
0.051119	0.085462

Step 7: Relative closeness to ideal solution can be calculated as:

$WF_1 = 0.99$ $WF_2 = 0.55$

$WF_3 = 0$ $WF_4 = 0.62$

The value closest to 1 provides us the best solution. So, considering workforce selection I_1 satisfies the workforce selection criteria. Different normalization methods can be adopted, and their result be

Normalization Methods	**Ranking results**
Vector Normalization	$WF_1 > WF_4 > WF_2 > WF_3$
Linear normalization (1)	$WF_1 > WF_4 > WF_2 > WF_3$
Linear normalization (2)	$WF_1 > WF_4 > WF_2 > WF_3$
Linear normalization (3)	$WF_1 > WF_4 > WF_2 > WF_3$

Table 4-3. Impact of normalization on ranking results

Chapter 5:

Conclusions and Future Works

5.1 Conclusion

Industry 4.0 is considered as the next phase in digitization and manufacturing sector. Implementing industry 4.0 is important to face the competition in the manufacturing world but implementing it in right direction is even more important. The goal of this study was to provide the methods which can be adopted by any industry for the implementation of industry 4.0 project. We addressed three main problems in this regard namely enterprise selection, project selection and workforce selection. TOPSIS and Genetic Algorithm based approaches are proposed. Direct ranking from experts were used to determine criteria weights. Numerical applications are provided. The proposed work is innovative and can be useful to manufacturing and service organizations interested in implementing Industry 4.0 projects for performance improvement.

5.2 Future work

This research has limitations which can be converted to opportunities for future works as follows:

- Inter-relationship between the evaluation criteria can be considered.
- AHP method could be used to prioritize the indicators
- The focus of this study was mainly on the manufacturing sector. It could be extended to other sectors.
- We have provided different solutions for the various problems associated with the implementation of industry 4.0 but these solutions have not been practically tested. They can be tested for different industry type, size and context.

- The assumptions we have considered are based on the previous literature and research. So, it can be modified according to the practical perspective and future usage.

References

[1] Alaba F., Othman M., Hashem I., Alotaibi F. (2017). Internet of things security: A survey. *Journal of Network and Computer Applications*, 88, 10-28.

[2] Alba, E., Laguna, M., Luque, G. Workforce planning with parallel genetic algorithm. Retrieved February 2018 from https://pdfs.semanticscholar.org/4b4e/aae134c26f9e530d7b768410d1aad5c819ea.pdf

[3] Abotaleb, I., Moussa, M., Hussain, S. (2014). Optimization of Allocating Multi-Skilled Labor Resources Using Genetic Algorithms. *CSCE General Conference,* 175, 1-9.

[4] Afshari, A., Mojahed, M., & Yusuff, R. M. (2010). Simple additive weighting approach to personnel selection problem. *International Journal of Innovation, Management and Technology,* 1(5), 511.

[5] Albach, H., Meffert, H., Pinkwart, A., Reichwald, R. Management of permanent change. Retrieved from https://link.springer.com/book/10.1007/978-3-658-05014-6.

[6] Algethami, H., Pinheiro, R.L., Landa-Silva, D. (2016). A Genetic Algorithm for a Workforce Scheduling and Routing Problem. *IEEE Congress on Evolutionary Computation(CEC),*927-934. Retrieved February 2018 from https://ieeexplore.ieee.org/document/7743889/.

[7] Alguliyev, R. M., Aliguliyev, R. M., & Mahmudova, R. S. (2015). Multicriteria personnel selection by the modified fuzzy VIKOR method. *The Scientific World Journal*, Retrieved December 2018, https://www.hindawi.com/journals/tswj/2015/612767/abs/.

[8] Askin, R.G., Huang, Y. (1997). Employee training and assignment for facility reconfiguration. *Proceedings of Industrial Engineering Research Conference*,426. Retrieved March 2018 from https://asu.pure.elsevier.com/en/publications/employee-training-and-assignment-for-facility-reconfiguration.

[9] Asl, M.B., Khalolzadeh, A., Youshanlouei, H.R., Mood, M.M. (2012). Identifyingand ranking the effective factors on selecting Enterprise Resource Planning(ERP) system using the combined Delphi and Shannon Entripy approach. *Procedia- Social and Behavioural Sciences,* 41,513-520.

[10] Baležentis, A., Baležentis, T., & Brauers, W. K. (2012). Personnel selection based on computing with words and fuzzy MULTIMOORA. Expert Systems with applications, 39(9), 7961-7967.

[11] Barlatt, A.Y. (2009). Models and algorithms for workforce allocation and utilization (Doctoral dissertation), University of Michigan. Retrieved January 2018 from https://deepblue.lib.umich.edu/handle/2027.42/63864.

[12] Benesova, A., and Tupa, J. (2017). Requirements for education and qualification of people in industry 4.0. *27th International Conference on Flexible Automation and Intelligent Manufacturing, FAIM2017*, 11, 2195-2202.

[13] Bhadury, J., Mighty, EJ., Damar, H. (2000). Maximizing workforce diversity in project teams: A network flow approach. *International Journal of Management Science*, 28,143–153.

[14] Bley, K., Leyh, C. (2016). Digitization of German enterprises in the production sector- do they know how digitized they are.*22nd Americas Conference on Information System,*1-10. Retrieved November 2017 from https://www.researchgate.net/publication/305661673_Digitization_of_German_Enterprises_in_the_Production_Sector_-_Do_they_know_how_digitized_they_are.

[15] Brettel M., Friederichsen N., Keller M., Rosenberg M. (2014). How virtualization, decentralization and network building change the manufacturing landscape: an industry 4.0 perspective. *World Academy of Science, engineering and*

Technology International journal of information and communication engineering, 8(1), 37-44.
[16] Bruecker P., Bergh J., Belien J., Demeulemeester E. (2015). Workforce planning incorporating skills: State of the art. *European Journal of operational Research,* 243(1), 1-16.
[17] Bohanec, M., Rajkovi, V. Knowledge acquisition and explanation for multi-attribute decision making, Yugoslavia. Retrieved from http://kt.ijs.si/MarkoBohanec/pub/Avignon88.pdf.
[18] Boran, F. E., Genç, S., & Akay, D. (2011). Personnel selection based on intuitionistic fuzzy sets. *Human Factors and Ergonomics in Manufacturing & Service Industries,* 21(5), 493-503.
[19] Boran, F. E., Genç, S., Kurt, M., & Akay, D. (2009). A multi-criteria intuitionistic fuzzy group decision making for supplier selection with TOPSIS method. *Expert Systems with Applications,* 36(8), 11363-11368.
[20] Bouajaja, S., Dridi, N. (2017). A survey on human resource allocation problem and its applications. *Operational Research*, 17(2), 339-369.
[21] Buer, S. V., Strandhagen, J. O., & Chan, F. T. (2018). The link between Industry 4.0 and lean manufacturing: mapping current research and establishing a research agenda. *International Journal of Production Research,* 56(8), 2924-2940.
[22] Cai, X., Li, K.N. (2000). A genetic algorithm for scheduling staff of mixed skills under multi-criteria. *European Journal of Operational Research,* 125(2), 359-369.
[23] Celaschi, F. (2017). Advanced design-driven approaches for an industry 4.0 framework: The human-centred dimension of the digital industrial revolution. *Strategic Design Research Journal,* 10, 97-104.
[24] Celik, N., Lee, S., Mazhari, E., Son, YJ., Lemaire, R., Provan, K. (2011), Simulation-based workforce assignment in a multi-organizational social network for alliance-based software development. *Simulation Modelling Practice and Theory*, 19, 2169–2188.
[25] Cert, A., Enea, M., Galante, G., Manuela, C. (2009). Multi-objective human resources allocation in R & D projects planning. *International Journal of Production Research,* 47(13), 3503-3523.
[26] Cesani, V.I., Steudel, H.J. (2005). A study of labor assignment flexibility in cellular manufacturing systems. *Computers and Industrial Engineering*, 48,571-591.
[27] Chen, J.Y., Tai, K.C., Chen, G.C. (2017). Application of programmable logic controller to build-up an intelligent industry 4.0 platform. *Procedia CIRP,* 63,150-155.
[28] Chryssolouris, G., Mavrikios, D., Papakostas, N., Mourtzis, D., Michalos, G., Georgoulias, K. (2009). Digital manufacturing: History, perspectives, and outlook. *Proceedings of Institution of Mechanical Engineers,* 223,451-462.
[29] Colarelli, S.M., Boos, A.L. (1992). AL. Sociometric and ability-based assignment to work groups: Some implications for personnel selection. *Journal of Organizational Behaviour*, 13,187–196.
[30] Collard, P., Gaspar. A., Clergue, M., Escazut, C. (1998). Fitness Distance Correlation, as statistical measure of Genetic Algorithm difficulty, revisited. *European conference on Artificial Intelligence.*927-93. Retreived March 2018from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.28.2481&rep=rep1&type=pdf.
[31] Crispim, J. A., & Pinho de Sousa, J. (2009). Partner selection in virtual enterprises: a multi-criteria decision support approach. *International Journal of Production Research,* 47(17), 4791-4812.

[32] Cuevas, R., Ferrer, J. C., Klapp, M., Muñoz, J. C. (2016). A mixed integer programming approach to multi-skilled workforce scheduling. *Journal of Scheduling*, 19(1), 91-106.
[33] Dağdeviren, M. (2010). A hybrid multi-criteria decision-making model for personnel selection in manufacturing systems. *Journal of Intelligent Manufacturing, 21(4), 451-460.*
[34] Dağdeviren, M., & Yüksel, İ. (2007). Personnel selection using analytic network process. *İstanbul Ticaret Üniversitesi Fen Bilimleri Dergisi*, 6(11), 99-118.
[35] Daghouri, A., Mansouri, K., Qbadou, M. (2018). Information system performance evaluation and optimization using AHP and TOPSIS: Construction industry case. *4th International Conference on Optimization and Applications(ICOA).* Retrieved June 2018 from https://ieeexplore.ieee.org/document/8370589/.
[36] Dilberoglu, U.M., Gharehpapagh, B., Yaman, U., Dolen, M.et al. (2017). The role of additive manufacturing in the era of Industry 4.0. *27th International Conference on Flexible Automation and Intelligent Manufacturing, FAIM2017,* 11,545-554.
[37] Dulmin, R., Mininno, V. (2003). Supplier selection using a multi-criteria deciaion aid method. *Journal of Purchasing and Supply Management* .9(4), 177-187.
[38] Dursun, M., & Karsak, E. E. (2010). A fuzzy MCDM approach for personnel selection. *Expert Systems with applications*, 37(6), 4324-4330.
[39] Efe, B. (2016). An integrated fuzzy multi criteria group decision making approach for ERP system selection. *Applied Soft Computing.* 38, 106-117.
[40] Eitzen, G, Panton, D, Mills, G. (2004). Multi-Skilled Workforce Optimization. *Annals of Operations Research*, 217, 359–372.
[41] Erol, S., Schumacher, A., Sihn, W. (2015). Strategic guidance towards Industry 4.0 – a three-stage process model. *International Conference on Competitive Manufacturing,* Retrieved September 2017 from http://publica.fraunhofer.de/documents/N-382579.html.
[42] Farahani et al. (2016). Car sales forecasting using neural networks and analytical hierarchy process. *The fifth international conference on Data analytics*, USA, 57-62.
[43] Fettermann, D. C., Cavalcante, C. G. S., Almeida, T. D. D., & Tortorella, G. L. (2018). How does Industry 4.0 contribute to operations management?. *Journal of Industrial and Production Engineering*, 35(4), 255-268.
[44] Flatt, H., Schriegel, S., Jasperneite, J., Trsek, H., Adamczyk, H. (2016). Analysis of the Cyber-Security of industry 4.0 technologies based on RAMI 4.0 and identification of requirements. *IEEE 21st International Conference on Emerging Technologies and Factory Automation (ETFA).* Retrieved March 2018 from https://ieeexplore.ieee.org/document/7733634/.
[45] Forman, E., Peniwati, K., (1998). Aggregating individual judgements and priorities with the analytical hierarchy process. *European Journal of Operational Research,* 108(1), 165-169.
[46] Fini, A.A.F., Rashidi, T.H., Akbarnezhad, A., Waller S.T. (2015). Incorporating multiskilling and learning in the optimization of crew composition. *Journal of Construction Engineering and Management*, 142(5), 1-14.
[47] FitzHugh, K.L.M., Piercy, N.F. (2013). Does collaboration between sales and marketing affect business performance? 207-220. Retrieved May 2018 from https://www.tandfonline.com/doi/abs/10.2753/PSS0885-3134270301.

[48] Fowler, J.F., Wirojanagud, P., Gel, E.S. (2008), Heuristics for workforce planning with worker differences. *European Journal of Operational Research*, 190, 724–740.
[49] Geissbauer, R., Schrauf, S. (2018). Industry 4.0: building the digital enterprise. *Global Digital Operations Study,* Retrieved August 2017 from https://www.pwc.com/gx/en/industries/industry-4-0.html.
[50] Gerbert, P., Lorenz, M., Rubmann, M. (2015). Industry 4.0: the future of productivity and growth in manufacturing industries. *The Boston Consulting Group.* Retrieved August 2017 from *https://www.bcg.com/enca/publications/2015/engineered_products_project_business_industry_4_future_productivity_growth_manufacturing_industries.aspx.*
[51] Gokalp, M.O., Kayabay, K., Akyol, M.A., Eren, P.E., Kocyigit, A. (2016). Big data for industry 4.0: A conceptual framework. *International Conference on Computational Science and Computational Intelligence(CSCI),* 431-434.
[52] Gomar, JE., Haas, CT., Morton, DP. (2002). Assignment and allocation optimization of partially multiskilled workforce. *Journal of Construction Engineering and Management,* 128, 103-109.
[53] Gorecky, D., Schmitt, M., Loskyll, M., Zuhlke, D. (2014). Human-machine-interaction in the industry 4.0 era. *12th IEEE International Conference on Industrial Informatics(INDIN).* Retreived June 2018 from from https://www.researchgate.net/publication/286571545_Human-machine-interaction%20in%20the%20industry%2040%20era.
[54] Gunasekaran A., Subramanian N., Papadopoulos T. (2017). Information technology for competitive advantage within logistics and supply chains: A review. *Transportation Research Part E: Logistics and Transportation Review*, 99, 14-33.
[55] Guoping, L.,Yun, H., Aizhi, W. (2017). Fourth industrial revolution: Technological drivers, impacts and coping methods. *Published in www.Springer.com. 27(4)*, 626-637.
[56] Haddara, M. (2014). ERP selection: The smart way. *Procedia Technology* .16, 394-403.
[57] Han, D., Han, I. (2004). Prioritization and selection of intellectual capital measurement indicators using analytic hierarchy process for the mobile telecommunications industry. *Expert Systems with Applications. 26, 519-527.*
[58] Haas, C. T., Rodriguez, A. M., Glover, R., Goodrum, P. M. (2001). Implementing a multiskilled workforce. *Construction Management & Economics*, 19(6), 633-641.
[59] Harbi, K.M. (2001). Application of the AHP in project management, *International Journal of Project Management*, 19, 19-27.
[60] Hasan, M. A., Shankar, R., & Sarkis, J. (2008). Supplier selection in an agile manufacturing environment using data envelopment analysis and analytical network process. *International Journal of Logistics Systems and Management,* 4(5), 523-550.
[61] Hecklau F., Galeitzkea M., Flachsa S., Kohlb H. (2016). Holistic approach for human resource management in industry 4.0. *Procedia CIRP, 54, 1-6.*
[62] Hermann, M., Pentek, T., Otto, B. (2016). Design principles for industry 4.0 scenarios. *49th Hawaii International Conference on System Sciences (HICSS)*, 3928-3937. Retrieved March 2018 from https://ieeexplore.ieee.org/document/7427673/.
[63] Hopp, WJ., Van, MP. (2004). Agile workforce evaluation: A framework for cross-training and coordination. *IIE Transaction,* 36,919.

[64] Hyari, K., El-Mashaleh, M., Kandil, A. (2010). Optimal assignment of multiskilled labor in building construction projects. *International Journal of construction education and research*. 6(1), 70-80.
[65] Hyldegard, J. (2006). Collaborative information behaviour exploring Kuhlthau's information search process model in a group-based educational setting. *Information Processing and Management,* 42,276–298.
[66] Joshi, A., Jackson, S.E. (2003). Managing workforce diversity to enhance cooperation in organizations. *International Handbook of Organizational Teamwork and Cooperative Working*, 277–296. Retrieved April 2018 from https://onlinelibrary.wiley.com/doi/pdf/10.1002/9780470696712.ch14.
[67] Ji, P., Zhang, H. Y., & Wang, J. Q. (2018). A projection-based TODIM method under multi-valued neuromorphic environments and its application in personnel selection*. Neural Computing and Applications*, 29(1), 221-234.
[68] Jun (2010). Multi-objective optimization for resource driven scheduling in construction projects. *University of Illinois at Urbana-Champaign*. Retrieved April 2018 from https://core.ac.uk/download/pdf/4825454.pdf.
[69] Kabak, M. (2013). A Fuzzy DEMATEL-ANP Based Multi Criteria Decision Making Approach For Personnel Selection. *Journal of Multiple-Valued Logic & Soft Computing,* 20(5), 571-593.
[70] Karre H., Hammera M., Kleindiensta M., Ramsauera, C. (2017). Transition towards an Industry 4.0 state of the Lean Lab at Graz University of Technology.*7th Conference on Learning Factories*, 9,206-213.
[71] Karsak, E. E. (2001). Personnel selection using a fuzzy MCDM approach based on ideal and anti-ideal solutions. *In Multiple criteria decision making in the new millennium* ,393-402. Retrieved November 2018 from https://link.springer.com/chapter/10.1007/978-3-642-56680-6_36.
[72] Ketabchi, S., Moosaei, H., Fallahi, S. (2013). Optimal error correction of the absolute value equation using a genetic algorithm. *Mathematical and Computer Modelling,* 57, 2339-2342.
[73] Khan M., Salah K. (2018). IoT security: Review, block chain solutions, and open challenges. *Future Generation Computer Systems*, 82,395-411.
[74] Killic, H.S., Zaim, S., Delen, D. (2015). Selecting "The Best" ERP system for SMEs using a combination of ANP and PROMETHEE methods. *Expert Systems with applications.*42(5), 2343-2352.
[75] Kim, H., Hwang, Y., Kim, K. (2014). Study on the application of multi-skilled labors to factory production process for securing economic feasibility of modular unit. *Korean Journal of Construction Engineering and Management*, 15(1), 11-19.
[76] Kinzel, H. Industry 4.0- Where does this leave the human factor. Retrieved October 2017 from https://tci-thaijo.org/index.php/JUCR/article/view/108399/85751.
[77] Konak, A., Coit, D.W., Smith, A.E. (2006). Multi-objective optimization using genetic algorithms: A tutorial. *Reliability Engineering & System Safety,* 91,992-1007.
[78] Koutra, G., Barbounaki, S., Kardaras, D., & Stalidis, G. (2017, July). A multicriteria model for personnel selection in maritime industry in Greece. *In Business Informatics (CBI), 2017 IEEE 19th Conferenc*e, Vol. 1, pp. 287-294.
[79] Kundakcı, N. (2016). Personnel selection with grey relational analysis. *Management Science Letters*, 6(5), 351-360.
[80] Kusumawardani, R.P., Agintiara, M. (2015). Application of Fuzzy AHP-TOPSIS Method for Decision Making in Human Resource Manager Selection Process. *Procedia Computer Science,* 72,638-646.

[81] Lee, J.W., Kim, S.H. (2001). An integrated approach for interdependent information system project selection. *International Journal of Project Management*. 19(2), 111-118.
[82] Leyh, C., Schaffer, T., Bley, K., Forstenhausler, S. (2016). SIMMI 4.0- A maturity model for classifying the enterprise-wide IT and software landscape focussing on industry 4.0. *Federated Conference on Computer Science and Information Systems (FedCSIS),* 8, 1297-1302.
[83] Liao, C.N., Kao, H.P. (2011). An integrated fuzzy TOPSIS and MCGP approach to supplier selection in supply chain management. *Expert Systems with Applications*. 38(9). 10803-10811.
[84] Liao, Y., Deschamps, F., Loures, E. D. F. R., & Ramos, L. F. P. (2017). Past, present and future of Industry 4.0-a systematic literature review and research agenda proposal. *International journal of production research*, 55(12), 3609-3629.
[85] Lill, I. (2009). Multiskilling in construction-a strategy for stable employment. *Technological and Economic Development of Economy*, 15(4), 540-560.
[86] LimaJunior, F.R., Osiro, L., Carpinetti, L.C.R. (2014). A comparison between Fuzzy AHP and Fuzzy TOPSIS methods to supplier selection. *Journal of Applied Soft Computing,* 21, 194-209.
[87] Lin, C.M., Gen, M. (2008). Multi-criteria human resource allocation for solving multistage combinatorial optimization problems using multi-objective hybrid genetic algorithm. *International Journal of Expert Systems with Applications,* 34, 2480-2490.
[88] Lin, C.H. (2013). A rough penalty genetic algorithm for constrained optimization. *Journal of Information Sciences,* 241, 119-137.
[89] Liu, C., Xu, X. (2017). Cyber-physical machine tool- the era of machine tool 4.0. *The 50th CIRP conference on manufacturing system,* 63, 70-75.
[90] Lin, H. T. (2010). Personnel selection using analytic network process and fuzzy data envelopment analysis approaches. *Computers & Industrial Engineering,* 59(4), 937-944.
[91] Longo, F., Nicoletti, L., Padovano, A. (2017). Smart operators in industry 4.0: A human-centred approach to enhance operators' capabilities and competencies within the new smart factory context. *Computers and Industrial Engineering*. 113,144-159.
[92] Lorenz, M., Gerbert, P., Rubmann, M. (2015). Industry 4.0: the future of productivity and growth in manufacturing industries. Retrieved January 2018 from https://www.bcg.com/en-ca/publications/2015/engineered_products_project_business_industry_4_future_productivity_growth_manufacturing_industries.aspx.
[93] Luque, G.,Alba, E. (2005). Workforce Planning with a Parallel Genetic Algorithm. *Studies in Computational Intelligence,* 367, 115-134.
[94] Masdefiol, R., del Mar, M., & Stävmo, F. (2016). Industry 4.0–Only designed to fit the German automotive industry: A multiple case study on the feasibility of Industry 4.0 to Swedish SMEs. Retrieved February 2018 from http://hj.diva-portal.org/smash/record.jsf?aq2=%5B%5B%5D%5D&c=186&af=%5B%5D&searchType=SIMPLE&query=&language=sv&pid=diva2%3A933316&aq=%5B%5B%7B%22organisationId%22%3A%22139%22%7D%5D%5D&sf=all&aqe=%5B%5D&sortOrder=author_sort_asc&onlyFullText=false&noOfRows=50&dswid=689.
[95] Masoni, R., Ferrise, F., Bordegoni, M., Gattullo, M., Uva A.E., Fiorentino, M., Carrabba, E., Donato, M.D. (2017). Supporting remote maintenance in industry 4.0 through augmented reality. *27th International Conference on Flexible Automation and Intelligent Manufacturing, FAIM201,* 11, 1296-1302.

[96] Maturana, S., Alarcón, L. F., Deprez, M. (2003). Modelling the impact of multiskilling and concrete batch size in multi-storey buildings. *In Proceedings of the XI Conference on Lean Construction, IGLC*, 11,553-566.
[97] McCall, J. (2004). Genetic algorithms and modelling. *Journal of Computational and Applied Mathematics,* 184,205-222.
[98] Meade, L.M., Presley, A. (2002). R & D project selection using the analytic network process. *IEEE Transactions on Engineering Management*, 49(1), 59-66.
[99] Mitchell, M. (1996). An Introduction to Genetic Algorithms. *MIT Press Cambridge,205.* Retrieved February 2018 from https://mitpress.mit.edu/books/introduction-genetic-algorithms.
[100] Motyl B., Baronio G., Uberti S., Speranza D. (2017). How will change the future engineer's skills in the industry 4.0 framework? A questionnaire surveys. *Procedia Manufacturing,* 11, 1501-1509.
[101] Naveh, Y, Richter, Y, Altshuler, Y, Gresh, DL, Connors, DP. (2007) Workforce optimization: Identification and assignment of professional workers using constraint programming. *IBM Journal of Research and Development*, 51,263–279.
[102] Nie, H., Liu. B. (2013). Combining MILP with Memetic Algorithm for Scheduling and Staffing Construction Project with a Multi-skilled Workforce. *International Conference on Computational and Information Sciences (ICCIS)*, 1150-1153. Retrieved October 2018 from https://ieeexplore.ieee.org/document/6643222/.
[103] Nowotarski, P., & Paslawski, J. (2017, October). Industry 4.0 concept introduction into construction SMEs. *In IOP Conference Series: Materials Science and Engineering*, 245(5). Retrieved December 2018 from http://iopscience.iop.org/article/10.1088/1757-899X/245/5/052043.
[104] Nurcin, C., Xi, H., Xu, D., Son Y.J., Lemaire, R., Provan, K. (2011). Simulation-based workforce assignment considering position in a social network, Simulation, 88(1), 72 – 96. Retrieved February 2018 from https://dl.acm.org/citation.cfm?id=2433909.
[105] Hester, P.T., Velasquez, M. (2013). An analysis of multi-criteria decision-making methods. *International Journal of Operations Research*. 10(2). 56-66.
[106] Pereshybkina, A., Conde, M. E. C., & Kalyesubula, T. (2017). How will the industry 4.0 transformations affect SMEs in Germany by 2030? Retrieved January 2018 from
https://opus.hsfurtwangen.de/.../Project+A_Scenario+Industry+4.0+and+SMEs_EK2.
[107] Pitic, L., Popescu, S., Pitic, D. (2014). Roadmap for ERP evaluation and selection. *Procedia Economics and Finance. 15, 1374-1382.*
[108] Radziwon, A., Bilberg, A., Bogersa, M., Madsen, E.S. (2014). The Smart Factory: Exploring Adaptive and Flexible Manufacturing. *Procedia Engineering,* 69, 1184-1190.
[109] Reid, D.J. (1996). Genetic Algorithms in Constrained Optimization. *Journal of Mathematical and Computer Modelling,* 23, 87-111.
[110] Roblek, V., Meško, M., & Krapež, A. (2016). A complex view of industry 4.0. Sage Open, 6(2). Retrieved January 2018 from http://journals.sagepub.com/doi/abs/10.1177/2158244016653987.
[111] Ross, E. (2017). Cross-trained workforce planning models (Doctoral dissertation, Lancaster University). Retrieved June 2018 from http://www.research.lancs.ac.uk/portal/en/publications/crosstrained-workforce-planning-models(bcb8d06c-be3f-4517-81e8-699953bd62a0).html.
[112] Russoa, F.S.M., Camanho, R. (2015). Criteria in AHP: A Systematic Review of Literature, *Procedia Computer Science*, 55, 1123-1132.

[113] Saaty, T.L., Peniwati, K., Shang, J.S. (2007). The analytic hierarchy process and human resource allocation: Half the story. *Journal of Mathematical and Computer Modelling,* 46, 1041-1053.

[114] Sadeghzadeh K., Salehi M. (2011). Mathematical analysis of fuel cell strategic technologies development solutions in the automotive industry by the TOPSIS multi-criteria decision-making method. *International journal of Hydrogen Energy,* 36(20), 13272-13280.

[115] Samaranyake, P., Ramanathan, K., Laosirihongthong, T. (2017). Implementing Industry 4.0 - A Technological Readiness Perspective. *International conference on Industrial Engineering and Engineering Management (IEEM)*,529-533. Retrieved October 2017 from https://ieeexplore.ieee.org/document/8289947/.

[116] Sampson, SE. (2006). Optimization of volunteer labor assignments. *Journal of Operations Management*, 24, 363–377.

[117] Santos, M. Y., e Sá, J. O., Andrade, C., Lima, F. V., Costa, E., Costa, C., ... & Galvão, J. (2017). A Big Data system supporting Bosch Braga Industry 4.0 strategy. *International Journal of Information Management*, 37(6), 750-760.

[118] Sari, B., Sen, T., & Kilic, S. E. (2008). Ahp model for the selection of partner companies in virtual enterprises. *The International Journal of Advanced Manufacturing Technology*, 38(3-4), 367-376.

[119] Sarkis, J., Talluri, S., & Gunasekaran, A. (2007). A strategic model for agile virtual enterprise partner selection. *International Journal of Operations & Production Management*, 27(11), 1213-1234.

[120] Sepehr, A., Zucca, C. (2012). Ranking desertification indicators using TOPSIS Algorithm. *Natural Hazards: Journal of International Society for the Prevention and Mitigation of Natural Hazards,* 62, 1137-1153.

[121] Schumacher A., Erol S., Sihn W. (2016). A maturity model for assessing industry 4.0 readiness and maturity of manufacturing enterprises. *Procedia CIRP, 52,161-166.*

[122] Sha, D. Y., & Che, Z. H. (2005). Virtual integration with a multi-criteria partner selection model for the multi-echelon manufacturing system. *The International Journal of Advanced Manufacturing Technology,* 25(7-8), 793-802.

[123] Shahin A., Mahbod M. (2007). Prioritization of key performance indicators. *International Journal of Productivity and Performance Management.* 56(3), 226-240.

[124] Shih H-S, Shyur H-J, Stanley Lee E.(2007), An extension of TOPSIS for group decision making, *Mathematical and Computer Modelling,* 45, 801–813.

[125] Simons, S., Abe, P., Neser, S. (2017). Learning in the AutFab- the fully automated industrie 4.0 learning factory of the University of Applied Science Darmstadt. *7th conference on learning factories,* 9, 81-88.

[126] Sniderman, B., Mahto, M., Cotteleer, M. (2016). Industry 4.0 and manufacturing ecosystems. Exploring the world of connected enterprises. Retrieved September 2017 from https://www2.deloitte.com/insights/us/en/focus/industry-4-0/manufacturing-ecosystems-exploring-world-connected-enterprises.html.

[127] Sureeyatanapas, P., Sriwattananusart, K., Niyamosoth, T., Sessomboon, W., Arunyanart, S. (2018). Supplier selection towards uncertain and unavailable information: An extension of TOPSIS method. *Journal Operations Research Perspectives,* 5, 69-79.

[128] Su, X., Hu, Y., Huang, S., Mahadevan, S., Deng, Y. (2014). A new decision-making method by incomplete preferences based on evidence distance. *Knowledge-Based System*, 56,264-272.

[129] Subramanian, P., Ramanathan, K., Laosirihongthong, T. (2012). A review of applications of Analytic Hierarchy Process in operations management. *International Journal of Production Economics*, 138, 215-241.

[130] Sundar, D., Umadevi, B., Alagarsamy, K. (2010). Multi Objective Genetic Algorithm for the Optimized Resource Usage and the Prioritization of the Constraints in the Software Project Planning. *International journal of Computer Applications*, 3, 1-4.

[131] Sung, T.K. (2018). Industry 4.0: A Korea perspective. *Journal of Technological Forecasting and Social Change,* 132, 40-45.

[132] Thannimalai, P., Kadhum, M.M., Feng, C.J., Ramadass, S. (2013). A glimpse of cross training models and workforce scheduling optimization. 2013 IEEE Symposium on Computers & Informatics, 98-103. Retrieved May 2018 from https://ieeexplore.ieee.org/abstract/document/6612383/.

[133] Tsai, C.W., Lai, C.F., Chiang, M.C., Yang, L.T. (2013). Data mining for internet of things: a survey. IEEE Communications Surveys & Tutorials. 16(1), 77-97.

[134] Vaidya, O.S., Kumar, S. (2006). Analytic hierarchy process: An overview of applications. *European Journal of Operational Research,* 169, 1-29.

[135] Vafaeipour, M., Zolfani, S.H., Varzandeh, M.H.M., Derakhti, A., Eshkalag, M.K. (2014). Assessment of regions priority for implementation of solar projects in Iran: New application of a hybrid multi-criteria decision-making approach. *Journal of Energy Conversion and Management,* 86, 653-663.

[136] Verdecho, M. J., Alfaro-Saiz, J. J., Rodriguez-Rodriguez, R., & Ortiz-Bas, A. (2012). A multi-criteria approach for managing inter-enterprise collaborative relationships. *Omega*, 40(3), 249-263.

[137] Vidic, N.S. (2008). Developing methods to solve the workforce assignment problem considering worker heterogeneity and learning and forgetting, PhD Dissertation, University of Pittsburgh. Retrieved May 2018 from https://www.researchgate.net/publication/282259842_developing_methods_to_solve_the_workforce_assignment .problem_considering_worker_heterogeneity_and_learning_and_forgettingdeveloping _methods_to_solve_the_workforce_assignment_problem_considering_worker .

[138] Wan, J., Cai, H., Zhou, K. (2015). Industrie 4.0: Enabling Technologies. *International conference on intelligent computing and internet of things(ICIT).* Retrieved March 2018 from https://ieeexplore.ieee.org/document/7111555/.

[139] Walter, M., Zimmermann, J. (2016). Minimizing average project team size given multi-skilled workers with heterogeneous skill levels. *Computers & Operations Research*, 70, 163-179.

[140] Wei, C.C., Chien, C.F., Wang, M.J.J. (2005). An AHP-based approach to ERP system selection. *International Journal of Production Economics*. 96(1), 47-62.

[141] Wittenberg, C. (2016). Human-CPS interaction-requirements and human-machine interaction methods for the industry 4.0. *IFAC,* 49, 420-425.

[142] Wright, J., Alajmi, A. (2016). Efficient Genetic Algorithm sets for optimizing constrained building design problem. *International Journal of Sustainable Built Environment,* 5, 123-131.

[143] Wong C., Sancha C., Thomson, C. (2017). A national culture perspective in the efficacy of supply chain integration practices. *International Journal of production economics*, 193,554-565.

[144] Wongwai, N., Malaikrisanachalee, S. (2011). Augmented heuristic algorithm for multi-skilled resource scheduling. *Automation in Construction*, 20, 429–445.

[145] Wu, C., & Barnes, D. (2011). A literature review of decision-making models and approaches for partner selection in agile supply chains. *Journal of Purchasing and Supply Managemen*t, 17(4), 256-274.
[146] Wu, C., & Barnes, D. (2012). A dynamic feedback model for partner selection in agile supply chains. *International Journal of Operations & Production Management,* 32(1), 79-103.
[147] Wu, C., Barnes, D., Rosenberg, D., & Luo, X. (2009). An analytic network process-mixed integer multi-objective programming model for partner selection in agile supply chains. *Production Planning and Control*, 20(3), 254-275.
[148] Wu, C., & Barnes, D. (2010). Formulating partner selection criteria for agile supply chains: A Dempster–Shafer belief acceptability optimization approach. *International Journal of Production Economics*, 125(2), 284-293.
[149] Xu X., Zhong R., Klotz E., Newman S., Thames L., Schaefer D. (2017). Intelligent manufacturing in the context of industry 4.0: A review. *Software -defined cloud manufacturing for industry 4.0*, 3(5), 616-630.
[150] Yan, H., Chai, H. (2017). Evaluation of influencing factors on general aviation tourism industry of xi'an based on AHP and fuzzy comprehensive evaluation method. *IEEE International Conference on Industrial Engineering and Engineering Management.* Retrieved from https://ieeexplore.ieee.org/document/8290198/.
[151] Zhang, S. F., & Liu, S. Y. (2011). A GRA-based intuitionistic fuzzy multi-criteria group decision making method for personnel selection. *Expert Systems with Applications*, 38(9), 11401-11405.
[152] Zhang, M., Guo, H., Huo, B., Zhao, X., Huang, J. (2017). Linking supply chain quality integration with mass customization and product modularity. *International Journal of production economics*. Retrieved June 2018 from https://www.sciencedirect.com/science/article/pii/S0925527317300117.
[153] Zhang, Y. (2010). Research on human resource optimization based on genetic algorithm from perspective of two-way choice model. *International Conference on Educational and Information Technology.* Retrieved February 2018 from *https://ieeexplore.ieee.org/document/5607688/.*
[154] Zhiting, S., Yanming, S., Jiafu, W., Peipei, L. (2017). Data quality management for service-oriented manufacturing cyber-physical systems. *Computer and Electrical Engineering,* 64, 34-44.

APPENDIX A: QUESTIONNAIRE

This Questionnaire is designed for Enterprise, project and workforce selection. Different responses are collected from people working in different industries. We organised this survey to validate our results for enterprise selection, project selection and workforce selection.

Please rank the importance of following criteria on a scale of 1-10 for implementing large scale information technology project in an organization. The rank 1 represents the lowest score and 10 represents the highest score.

Your Sector: Service Type of industry: Home Automation

Years of experience with IT projects 5

Enterprise Selection

Criteria	Score (1-10), 1- Least important, 10- Most Important
Organization Type (manufacturing/service)	8
Organization Size (Large, Medium, SME)	7
Digital maturity level (state of IT implementation)	9
Digital (IT) strategy	9
Organization culture (international)	7
Innovation	10

Project Selection

Criteria	Score (1-10), 1- Least important, 10- Most Important
Implementation cost	7
Time to completion	10
Feasibility	10
Resource Requirements	9
IT Requirements	9
Expected Revenues	9
Risk	9

Workforce Selection

Criteria	Score (1-10), 1- Least important, 10- Most Important
Computer skills (programming, human machine interface)	10
Soft skills (communication)	8
Ability to work in different business units (multitasking)	8
Leadership	7
Core skills (fundamentals, engineering)	9
Team thinking	9
General aptitude (problem solving)	9

THANK YOU

Please rank the importance of following criteria on a scale of 1-10 for implementing large scale information technology project in an organization. The rank 1 represents the lowest score and 10 represents the highest score.

Your Sector: Manufacturing/Service   Type of industry: Manufacturing

Years of experience with IT projects: 1

Enterprise Selection

Criteria	**Score (1-10), 1- Least important, 10- Most Important**
Organization Type (manufacturing/service)	7
Organization Size (Large, Medium, SME)	8
Digital maturity level (state of IT implementation)	8
Digital (IT) strategy	8
Organization culture (international)	6
Innovation	6

Project Selection

Criteria	**Score (1-10), 1- Least important, 10- Most Important**
Implementation cost	9
Time to completion	7
Feasibility	5
Resource Requirements	6
IT Requirements	6
Expected Revenues	8
Risk	6

Workforce Selection

Criteria	**Score (1-10), 1- Least important, 10- Most Important**
Computer skills (programming, human machine interface)	6
Soft skills (communication)	5
Ability to work in different business units (multitasking)	5
Leadership	4
Core skills (fundamentals, engineering)	4
Team thinking	4
General aptitude (problem solving)	4

THANK YOU

Please rank the importance of following criteria on a scale of 1-10 for implementing large scale information technology project in an organization. The rank 1 represents the lowest score and 10 represents the highest score.

Your Sector: Manufacturing/Service: Service

Type of industry: Technology

Years of experience with IT projects: 7 years

Enterprise Selection

Criteria	**Score (1-10), 1-Least important, 10-Most Important**
Organization Type (manufacturing/service)	3
Organization Size (Large, Medium, SME)	7
Digital maturity level (state of IT implementation)	9
Digital (IT) strategy	10
Organization culture (international)	5
Innovation	8

Project Selection

Criteria	**Score (1-10), 1- Least important, 10-Most Important**
Implementation cost	8
Time to completion	5
Feasibility	7
Resource Requirements	4
IT Requirements	10
Expected Revenues	6
Risk	9

Workforce Selection

Criteria	**Score (1-10), 1- Least important, 10-Most Important**
Computer skills (programming, human machine interface)	9
Soft skills (communication)	5
Ability to work in different business units (multitasking)	6
Leadership	8
Core skills (fundamentals, engineering)	10
Team thinking	7
General aptitude (problem solving)	4

THANK YOU

Please rank the importance of following criteria on a scale of 1-10 for implementing large scale information technology project in an organization. The rank 1 represents the lowest score and 10 represents the highest score.

Your Sector: Manufacturing/Service   Type of industry: IT

Years of experience with IT projects 7

Enterprise Selection

Criteria	**Score (1-10), 1- Least important, 10- Most Important**
Organization Type (manufacturing/service)	10
Organization Size (Large, Medium, SME)	10
Digital maturity level (state of IT implementation)	9
Digital (IT) strategy	10
Organization culture (international)	5
Innovation	7

Project Selection

Criteria	**Score (1-10), 1- Least important, 10- Most Important**
Implementation cost	9
Time to completion	10
Feasibility	7
Resource Requirements	10
IT Requirements	9
Expected Revenues	9
Risk	5

Workforce Selection

Criteria	**Score (1-10), 1- Least important, 10- Most Important**
Computer skills (programming, human machine interface)	7
Soft skills (communication)	7
Ability to work in different business units (multitasking)	9
Leadership	9
Core skills (fundamentals, engineering)	9
Team thinking	6
General aptitude (problem solving)	6

THANK YOU

For the result validation of Genetic algorithm, we also used Python language to get the results. Following results were obtained.