Mathematical Models for Designing Integrated Sustainable Manufacturing Systems

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Abstract

Mathematical Models for Designing Integrated Sustainable Manufacturing Systems

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Sustainability may be defined as the attentive endeavor in avoidance of the depletion of natural resources. Sustainability is progressively becoming a topic of substantial interest in both academic and manufacturing environments. Due to the profitability in conducting sustainable practices and the legal pressure from the governments, many companies are going to be engaged in the product recovery business for retrieving materials and value-added features in used products. In designing sustainable manufacturing systems, hybrid manufacturing-remanufacturing systems can be applied as a result of their social, economic, and environmental effects. A sustainable manufacturing system should work as a part of a sustainable closed-loop supply chain. Hence, sustainable practices should be applied in both closed-loop supply chains and manufacturing systems simultaneously. The premier goal of this dissertation is to apply sustainable practices in designing a network consisting of a manufacturing system in a closed-loop supply chain in view of realistic assumptions; for example, alternative process routings, contingency process routings, lot splitting, reconfigurations, machine adjacency requirements, machine failures, reliability of machines, and quality of the returned products, outsourcing, as well as stochastic and probabilistic parameters. Four models are developed in this dissertation. The first model is a mixed-integer mathematical model for a third-party remanufacturer in a remanufacturing facility with cellular layout to be as a part of a closed-loop supply chain. This mathematical model is solved using an exact solution procedure through the use of branch-and-bound and branch-and-cut of CPLEX.

The second model is the extension of the first model by taking operation sequences, machine adjacency constraints, alternative process routings, and outsourcing option of the part demands into consideration. This mathematical model is solved using an exact solution procedure through the use of branch-and-bound and branch-and-cut of CPLEX. The third model is a mixed-integer mathematical model which is developed for an original equipment manufacturer in a hybrid manufacturing-remanufacturing facility with cellular layout considering alternative and contingency process routings to be as a part of a closed-loop supply chain. This mathematical model is solved using an exact solution procedure through the use of branch-and-bound and branch-and-cut of CPLEX. The fourth model is a stochastic mixed-integer mathematical model which is developed for a third party remanufacturer in a remanufacturing facility with cellular layout to be as a part of a sustainable closed-loop supply chain. A queuing-based approach is considered for the model in a Jackson queuing network. To avoid a long waiting time of the parts in the queuing system, a chance-constrained is added to the mathematical model as well. This mathematical model is solved using an exact solution procedure through the use of branch-and-bound and branch-and-cut of CPLEX. The mathematical models in this dissertation are mainly targeted to be used in industry at the operational level which would lead to further industrial applications mostly at the design stage of integrated manufacturing and supply chain systems in addition to the possible applications at the operational level. All the models in this dissertation have been formulated, solved, analyzed, together with this, sensitivity analyses for representing the usability of the models in practice have been presented.

Keywords: Sustainability, Sustainable design, Cellular manufacturing systems, Remanufacturing, Hybrid manufacturing-remanufacturing systems, Stochastic programming, Queuing theory, Reliability, Closed-loop supply Chain.

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Chapter 1 Introduction

1.1 Introduction

Sustainability is the main issue for companies to be successful in today's business world. In general, sustainability brings different meanings into minds such as green, clean, maintain, and retain, stability, ecological balance, natural resources and environment [101]. Sustainability is a perspective to meet the contemporary needs of the human communities across the globe without jeopardizing the ability of future generations to meet their own needs [102]. Sustainability per se refers to sustainable practices in economy, environment, and society. Therefore, environmental sustainability can be defined as the ecological integrity to consume natural resources of earth at a level where they are capable of replenishing themselves [103]. Economic sustainability refers to practices to assure the long-term economic growth without threatening the environmental and societal pillars of the sustainability [104]. Societal sustainability points out the availability of human rights and the basic necessities for people all over the world. Realizing societal sustainability requires committed country leaders who ensure personal, social, and cultural rights are valued and all people are protected from discrimination and racism [103].

In manufacturing systems, sustainability may be defined as producing products that use processes having less negative environmental impacts, safe for employees, conserving energy and natural resources, and economically sound [102]. Realizing sustainability in service and manufacturing enterprises requires not only a comprehensive investigation on the products and their fabrication processes but also the entire supply chain [105]. Due to the stringent awareness towards the preservation and resuscitation of natural resources and the potential economic benefits, designing sustainable manufacturing enterprises have become a critical issue in recent years. This presents different challenges in coordinating the activities inside the manufacturing systems with the entire closed-loop supply chain. A sustainable manufacturing system should operate as a part of a sustainable supply chain. A sustainable supply chain has two main characteristics. The first one is the reverse flows of returned products, modules, and components from consumers back to the companies along with the forward flows of the new and/or remanufactured products from the companies to the markets. The second characteristic of the closed-loop supply chains refers to the observation of sustainability pillars in designing supply chains that is economical, ecological and social aspects of an organization [105]. While sustainability has been a popular research field in closed-loop supply chains and reverse logistics, there has not been much emphasis on the design problems of sustainable manufacturing systems. For sustainable manufacturing systems, resorting to reconfigurable manufacturing systems and cellular manufacturing systems are highly recommended [105]. Reconfigurable manufacturing systems have been developed with the mindset of responding to sudden market changes or inherent system variabilities [106]. Hence, physical structure of the manufacturing system can be adjusted quickly to enhance the management of capacity and functionality.

To cope with different circumstances in production planning and facility design, different production layouts have been developed, namely functional (job-shop) layout, line layout, and cellular layout. Functional (job-shop) layout performs well in the case where the production variety is high and production volume is low. On the other hand, line layouts can be applied where the production variety is low and production volume is high. Cellular manufacturing as the application of group technology (GT) has been used in intermittent production systems including job-shop or batch-shop production to improve operations of the manufacturing system. Cellular manufacturing layouts are an appropriate selection to deal with the mid production volume and mid production variety. According to Gharbi [105], cellular manufacturing systems can highly enhance the efficiency of the manufacturing systems through the use of mass customization which contributes to improving the sustainability pillars. Mass customization refers to producing goods and services for individual needs of customers [105]. In conventional cellular manufacturing systems, the main assumption was to keep the product mix and part demand constant for the entire planning horizon. However, in the dynamic cellular manufacturing, a planning horizon can be divided into different periods where each period may have different product mix and part demands. There are many advantages in proper design and implementation of cellular layouts in manufacturing systems; for instance, reduction in part movements, set-up time, waiting time between operations, and work-in-process inventory [68]. “The presence of alternative processes routings is typical in many discrete, multi-batch, small lots size production environments” [10]. Resorting to alternative process routings increases the number of ways to form the manufacturing cells [10]. According to Kusiak [107], resorting to alternative process routings decreases the total number of available machines in the manufacturing system. To enhance the reliability of the cellular manufacturing systems, contingency process routings can be used along with the main process routings. By taking contingency process routings into consideration, manufacturing systems can run in an uninterrupted manner [16]. When contingency process routings are selected, production of the other part types in the main routings are not affected. Machines that are selected to be used in contingency process routings in a time period are completely different entities from the machines in the main process routings. Figure 1-1 shows the material flow in a cellular manufacturing system.

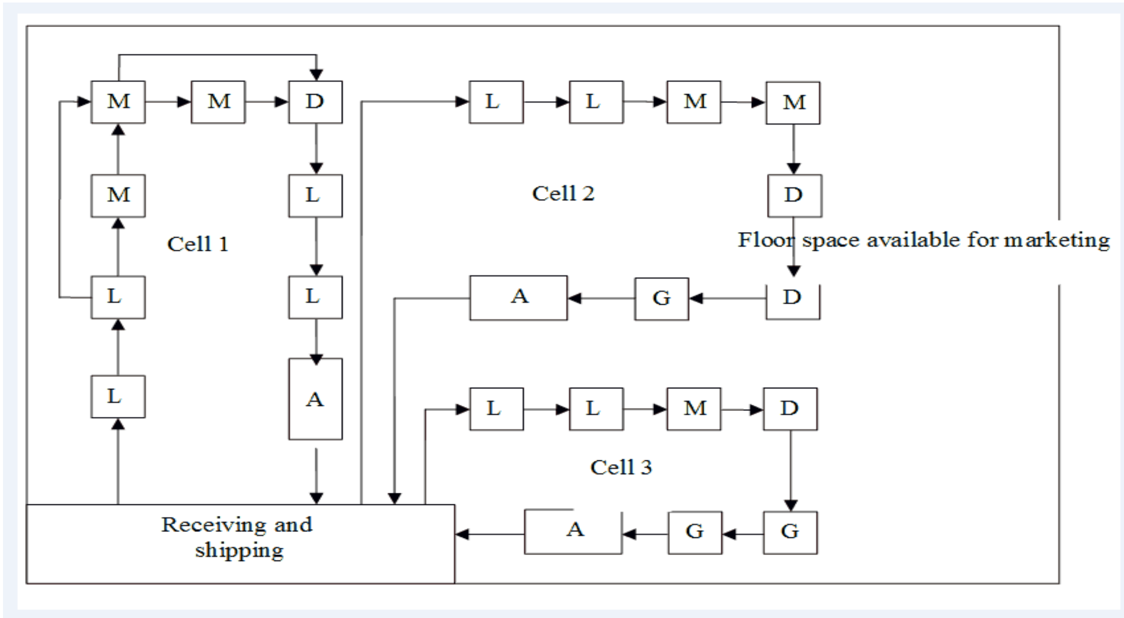

Figure 1-1 *Material flow in a Cellular Manufacturing System*

(www.whatissixsigma.net)

Remanufacturing is one of the main keys for companies to be successful in today's business world. Remanufacturing may be defined as a comprehensive industrial process by which a previously sold, damaged, or non-functional products or components are returned to a like-new or better-than-new conditions [108]. Such processes are used mainly in automotive and component manufacturing industries among many other industries. There are several processes contained in remanufacturing activities of a company such as disassembling to separate usable parts, cleaning, repairing and refurbishments [68]. There are many benefits for companies implementing remanufacturing operations including saving in labors, materials and energy costs, shorter production lead times, new market development opportunities, and a positive socially concerned image for firms [72]. In designing sustainable manufacturing systems, hybrid manufacturing-remanufacturing systems can also be applied because of their social, economic and environmental effects. In recent years, designing hybrid manufacturing-remanufacturing systems have become a topic of substantial interest due to the economic opportunities, social incentives, and environmental legislations. In practice, the majority of remanufacturing activities are performed by third-party remanufacturers (3PRs) [109]. Original equipment manufacturers (OEM) usually adopts two policies for remanufacturing their products such as outsourcing remanufacturing and authorization remanufacturing. In the outsourcing remanufacturing policy, a 3PR only carry out the remanufacturing operations, and the marketing activities of the remanufactured products is performed by the OEM itself [110]. In contrast, in the authorization remanufacturing policy, a 3PR acquires the exclusive rights from the OEMs to remanufacture end-of-life (EOL) products and resell the remanufactured products without the participation of the OEM [110].

In real-world manufacturing systems, decisions are made by taking uncertainties into considerations. Input parameters of the cell formation problems such as demand, processing times, and setup times should also encompass uncertainties. Stochastic optimization, queuing theory, and robust optimizations are the available approaches in designing uncertain mathematical models. Stochastic optimization refers to optimizing the objective function of mathematical models when randomness is present [111]. There are two types of decision variables in developing two-stage models; first stage decisions are taken without the full information on the random parameters, and second-stage decisions are taken later when full information is received on realizations (scenarios) of some random vectors [111].Queueing theory is the mathematical analyses of waiting lines, or queues [112]. Queueing theory, in general, is considered as a branch of operations research where the results of queuing analyses are often used to make decisions regarding the use of limited resources for providing a designated service level.

1.2 Problem statement and research objectives

According to Government of Canada [113], “Sustainable manufacturing promotes minimizing or eliminating production and processing wastes through eco-efficient practices, and encourages adopting new environmental technologies.” Hence, reconfigurable cellular manufacturing systems as a subsection of lean manufacturing can be applied in practice to minimize the wastes through the mass-customization. Closed-loop supply chains are inherently sustainable due to the post-use of components and materials of the returned products through remanufacturing and recycling in remanufacturing and/or hybrid manufacturing-remanufacturing facilities. Therefore, a sustainable manufacturing system should work as a part of a closed-loop supply chain to create a sustainable network for the whole enterprise.

According to the literature review presented in Chapter 2, it can be observed that:

- There is an abundant amount of research concerning the design issues of sustainable closed-loop supply chains and reverse logistics in the literature, yet research pertaining to the design issues of sustainable manufacturing systems is very limited;
- Research on modeling and optimization of cost-effective and reliable sustainable manufacturing systems taking outsourcing, alternative process routings, and contingency process routings into consideration has not been done in the literature.
- Research pertaining to the design of integrated reconfigurable cellular manufacturing systems with remanufacturing as the main recovery option and/or reconfigurable cellular hybrid manufacturing-remanufacturing systems are in the infancy era;

- There is not any related research article in the literature considering the uncertainty issues with the use of stochastic programming and queuing theory in designing integrated cellular manufacturing systems as a part of a closed-loop supply chains.

As noted previously, the use of reconfigurable cellular manufacturing systems in designing sustainable manufacturing systems is highly recommended in the literature. Remanufacturing process also is one of the leading resolutions in sustainable development of corporations. Remanufacturing, as one of the prevalent recovery options, aims at recovering value from the used products and reducing both the natural resources needed and the waste produced. Remanufacturing can take place in remanufacturing facilities and/or in hybrid manufacturing-remanufacturing facilities with the shared and limited resources for producing new and remanufactured products. In establishing a trend to circle back the discarded products into the value chain and minimizing the wastes in the landfilling area, closed-loop supply chains should be utilized in conjunction with manufacturing systems [115]. For designing closed-loop supply chains, recovery operations such as remanufacturing, refurbishing, and recycling are typically considered. This dissertation addresses to several interrelated concepts including cellular manufacturing systems, remanufacturing and hybrid manufacturing-remanufacturing systems, and closed-loop supply chains to design sustainable manufacturing systems as a part of a sustainable closed-loop supply chain. In view of the literature review, a mathematical model is developed in Chapter 3 considering a dynamic cellular manufacturing system as a part of a closed-loop supply chains where remanufacturing is considered to be the single recovery option. The mathematical model in Chapter 3 can be considered to be the basis of the mathematical models in the following chapters. In chapter 4, the mathematical model in Chapter 3 is extended with the consideration of outsourcing and alternative process routings to effectively improve the economic and environmental pillars of the sustainability. In Chapter 5, to incorporate the application of hybrid manufacturing-remanufacturing systems in the sustainable design of manufacturing systems and to extend the previous mathematical models, a detailed mathematical model is developed. Hence, a reconfigurable cellular hybrid manufacturing-remanufacturing system is developed in Chapter 5 where the consideration of alternative process routings and contingency process routings can improve the flexibility and reliability of the mathematical model to fulfil the part demands. In designing the integrated sustainable manufacturing and closed-loop supply chain systems, no researchers in the literature has developed a chance-constraint stochastic programming models considering queuing theory. The mathematical model in Chapter 6 is the static (single-period) and stochastic (scenario-based) version of the mathematical models proposed in Chapter 3 and Chapter 4.

The main purpose of this dissertation is to design well-organized sustainable manufacturing systems as a part of a sustainable closed-loop supply chain with realistic assumptions such as alternative process routings, contingency process routings, lot splitting, reconfigurations, machine adjacency requirements, machine failures, reliability of the machines, and quality of the returned products, outsourcing, as well as stochastic and probabilistic parameters.

The objectives of this dissertation are as follows:

- To review the papers related to deterministic and stochastic cellular manufacturing, remanufacturing and hybrid manufacturing-remanufacturing systems, and closed-loop supply chains and to summarize the conclusions and observations;
- To design and develop a third-party sustainable remanufacturing system as a part of a sustainable closed-loop supply chain;

- To design and develop a third-party sustainable manufacturing system as a part of a sustainable closed-loop supply chain featuring outsourcing and alternative process routings;
- To design and develop a sustainable and reliable hybrid manufacturing-remanufacturing as a part of a sustainable closed-loop supply chain considering reliability of machines, probabilistic parameters, alternative process routings, and contingency process routing.
- To design and develop a third-party sustainable remanufacturing system as a part of a sustainable closed-loop supply chain considering realistic assumptions such as reliability of the machines, stochastic and probabilistic parameters, and queuing theory to be as a part of a closed-loop supply chain.
- To solve the proposed integrated models and evaluate its solutions capability by solving different-sized instances of the mathematical models.

Figure 1-2 demonstrates the relations among the mathematical models as well as common and different properties in these modes models developed in this dissertation. In all the mathematical models, cellular layout, remanufacturing option, and a closed-loop supply chain configuration are considered. According to Figure 1-2, mathematical models have also several different properties including the nature of the parameters such as deterministic or stochastic, alternative and contingency process routings, outsourcing, and reliability of machines. Figure 1-3 shows the common material flow of the mathematical models proposed in this dissertation.

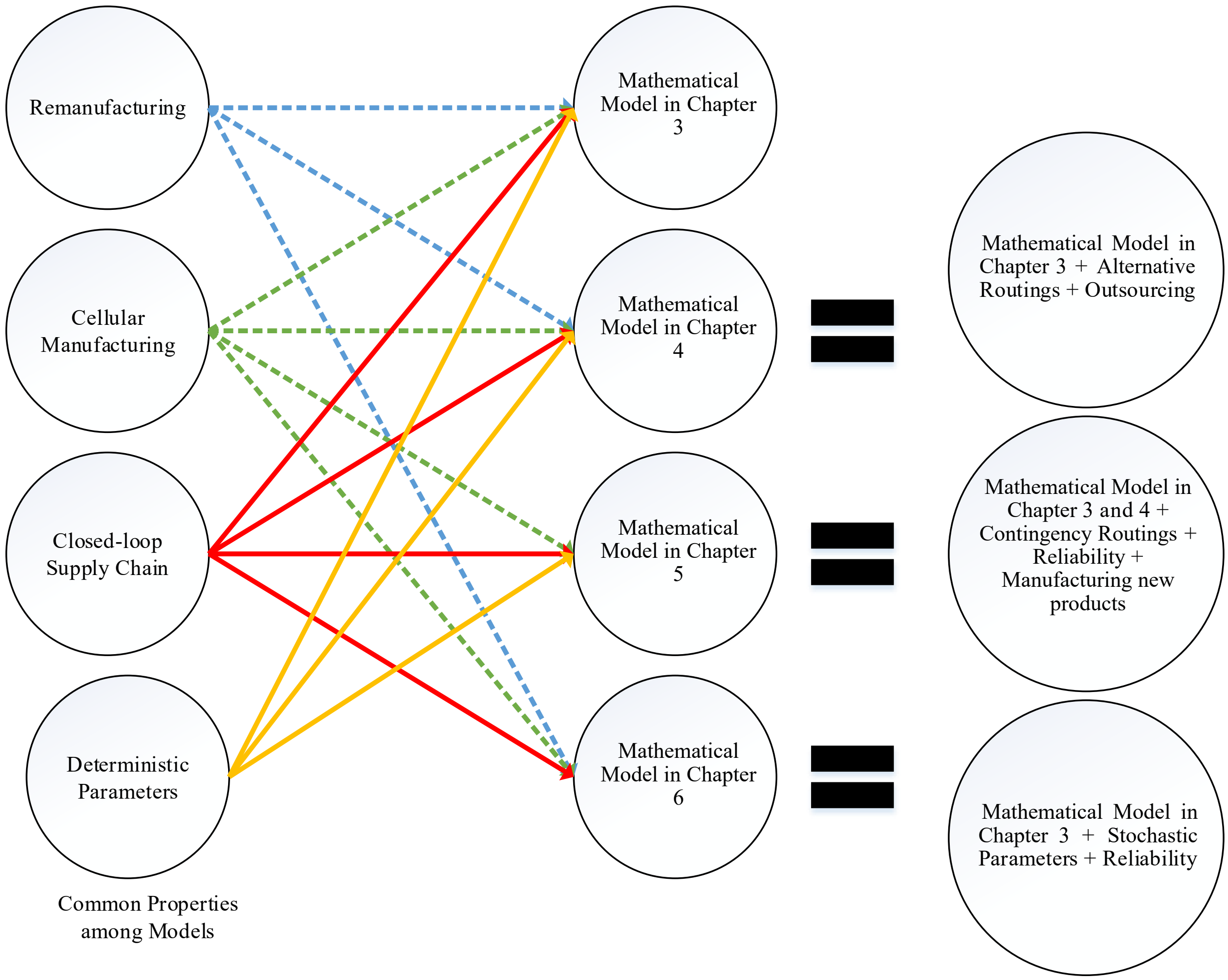

Figure 1-2 *Common and different properties of the mathematical models*

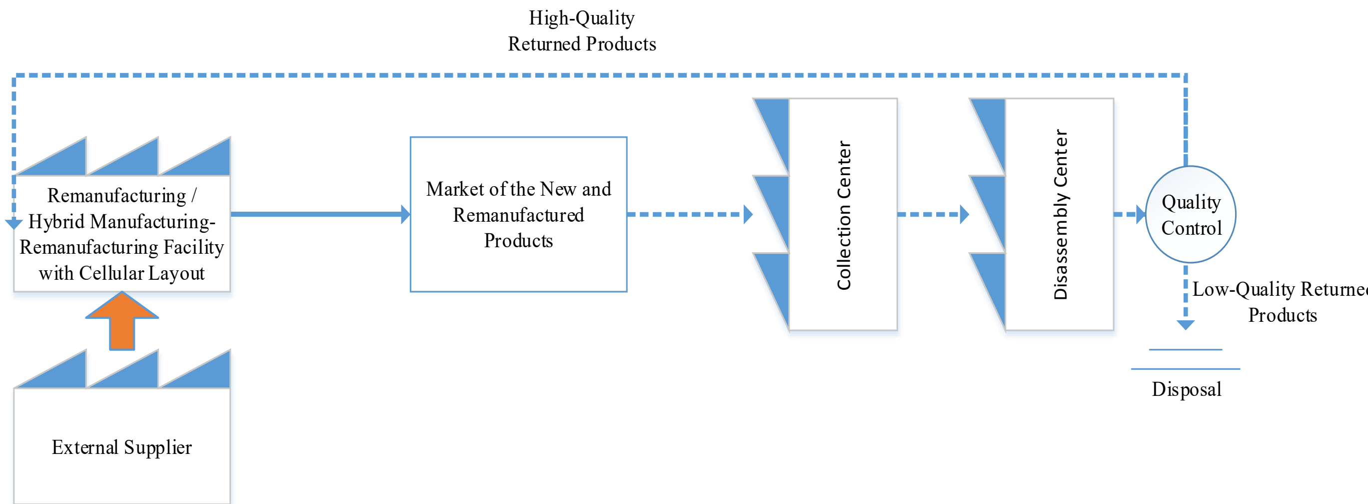

Figure 1-3 *Common material flow* of *the mathematical models*

1.3 Outline of thesis

Chapter 2 reviews and summarizes the existing research on deterministic and stochastic cellular manufacturing systems, remanufacturing and hybrid manufacturing-remanufacturing systems, and closed-loop supply chains. In chapter 3, a mixed-integer mathematical model is developed for a remanufacturing system in a closed-loop supply chain. Chapter 4 is the extension of the mathematical model presented in chapter 3, that is, alternative process routings and outsourcing are added to the model in chapter 3. In chapter 5, a mixed-integer mathematical model is developed for a hybrid manufacturing-remanufacturing as a part of a closed-loop supply chain. In chapter 6, a stochastic integer mathematical model is developed for a remanufacturing system. Chapter 7 presents the conclusions and future research directions of this dissertation.

Chapter 2 Literature Review

2.1 Introduction

Sustainability is the main issue for companies to be successful in today's business world. While sustainability is a well-known research topic in the closed-loop supply chains and reverse logistics, one cannot observe much emphasis on the sustainable design of the manufacturing systems. To build a sustainable manufacturing enterprise, a manufacturing system should work as a part of closed-loop supply chains. Cellular manufacturing systems, due to mass customization, are highly recommended to build a sustainable manufacturing system. Mass customization refers to the delivery of wide-market merchandises and services that have been modified to satisfy specific needs of customers [1]. In manufacturing systems, mass customization is a technique which combines the flexibility of process layout systems such as job-shop production systems with the benefits of the economy of scale in the product layout systems including transfer lines and/or assembly production systems [1]. In designing sustainable manufacturing systems, remanufacturing systems and/or hybrid manufacturing-remanufacturing systems can also be applied because of their constructive social, economic and environmental effects. Therefore, a review of the literature is done in this chapter of the following interrelated concepts:

- Dynamic cellular manufacturing systems;
- Stochastic cellular manufacturing systems;
- Remanufacturing and hybrid manufacturing-remanufacturing systems;
- Closed-loop supply chains.

2.2 Dynamic Cellular Manufacturing Systems

Cellular manufacturing as the application of group technology (GT) has been used in intermittent production systems including job-shop or batch-shop production to improve operations of the manufacturing system as well as to gain economic advantages of the mass production [1]. In static cellular manufacturing systems, the main assumption is to keep the product mix and part demand constant for the entire planning horizon. However, in the dynamic cellular manufacturing, a planning horizon can be divided into different periods where each period may have different product mixes and part demands. In this section, a review of the literature pertinent to deterministic dynamic cellular manufacturing systems is presented. We have investigated different research articles regarding several aspects of cellular manufacturing systems such as objectives, problem-solving approaches, and material handlings such as inter-cell and intra-cell movements. Purchek [2] was one of the first authors who introduced a Linear Programming (LP) model to formulate part/machine groups. Purchek's [2] p-median model is the first model to cluster n parts (machines) into p part families (machine cells) using mathematical programming. Rheault et al. [3] were the first to consider the concept of dynamic cell formation problem. They developed a mathematical model for scheduling a dynamic and turbulent manufacturing system. Their model encompasses five important modules such as part family formation, family sequencing, cellular configuration, job scheduling, and system monitoring and their objective function aims at minimizing the material handling cost and machines relocation costs. One of the important elements in designing a cellular manufacturing system is considering human issues since the lack of this factor can significantly reduce the benefits of the use of the cellular manufacturing systems. Nembhard [4] developed a heuristic worker-task assignment based on the individual worker learning rates in which two tasks were assigned. One with a long-production run to worker who learns very slowly and the other one with a short-production run to workers who learns most rapidly. Norman et al. [5] developed a mixed integer programming model for worker assignments in cellular manufacturing system incorporating different technical skills of the workers and their impacts on the system performance. Chen and Cao [6] presented a nonlinear mixed integer programming model to investigate the application of production planning problem in cellular manufacturing system. Their model aims at minimizing costs related to inter-cell material handling, manufacturing setup, cell setup, inventory holding and production planning. These authors developed a Tabu-Search (TS) algorithm to solve the model. Cao and Chen [7] developed a robust mathematical model for designing a cellular manufacturing system aims at minimizing machine cost and expected inter-cell material handling cost. They solved the mathematical model using a two-stage TS based algorithm. Tavakkoli-Moghaddam et al. [8] discussed the use of different metaheuristics including TS, Genetic Algorithm (GA), and Simulated Annealing (SA) to solve a nonlinear mixed integer cell formation problem. Results obtained demonstrated that SA has more accurate near-to-optimal solutions in a shorter average computational time. Tavakkoli-Moghaddam et al. [9] proposed a multi-objective dynamic cell formation problem including several important features of cellular design such as alternative process plan, operation sequences, and machine relocation. The objective function of their model determines the optimal number of cells, optimal amounts of machine relocation costs and optimal inter-cell movement costs in different time periods. Defersha and Chen [10] developed a comprehensive mathematical model for the design of a dynamic cellular manufacturing system. Their model includes several configuration elements such as lot-splitting, alternative process routings, sequence of operations, machine duplications, and work-load balancing among the cells. They solved the model with the use of LINGO optimization software. In another research work, Defersha and Chen [11] proposed a nonlinear mixed-integer mathematical model for designing a cellular manufacturing system. Their model incorporates dynamic cell configuration, alternative routings, lot splitting, sequence of operations, multiple units of identical machines, machine capacity, workload balancing among the cells, operation cost, subcontracting part processing cost, tool consumption cost, setup cost, cell size limits, and machine adjacency constraints. They solved the model with the use of LINGO commercial software for small-sized instances of the model. They applied GA for solving the larger instances of the model.

Saidi-Mehrabad and Safaei [12] presented a mathematical model for the design of a cellular manufacturing system. They used neural network approach to solve their model. Safaei et al. [13] developed a mixed-integer programming model for designing a dynamic cellular system. Their objective function encompasses different cost elements such as material handling cost, machine duplication (identical machines in different cells) cost, and the cost of alternative production schemes. They solved the mathematical model with the use of SA algorithm to get near-to-optimal solutions. Defersha and Chen [14] integrated a cellular manufacturing system with production lot sizing problem. They developed a mathematical model to minimize both production and quality related costs. They solved their model by using a linear programming approach embedded GA. In another study, Deferesha and Chen [15] developed a parallel GA approach to solve the cell formation problem in a dynamic environment. Computational results demonstrated the efficiency of the proposed approach over sequential GA and off-the-shelf optimization software. Ah kioon et al. [16] extended Defersha and Chen's [11] model by proposing a nonlinear mixed integer mathematical model by addressing formation of compact cells with the use of intra-cellular movement of parts. Several linearization techniques were followed to solve their mixed integer model. Ah kioon et al. [17] proposed a nonlinear mixed integer multi-period mathematical model for production planning of a dynamic cellular manufacturing system. They considered reconfiguration of the cells, operation sequences, duplicate machines, machine capacity, machine procurements, lot splitting and contingency process routings. They, for the first time, discussed the use of contingency process routings to prevent cellular manufacturing system works intermittently due to machine breakdowns and/or workload imbalance. Aryanezhad et al. [18] developed a nonlinear integer programming model for a dynamic cell formation problem considering worker assignment. Their model has two main components in the objective function including production costs, inter-cell material handling costs and machine costs in the planning horizon; and human issues considering hiring, firing, and training costs as well as salaries. Safaei and Tavakkoli-Moghaddam [19] developed a multi-period mathematical model for the design of a dynamic cellular manufacturing system aims at minimizing material handling, reconfiguration, subcontracting, inventory holding and machine costs. They solved the model with the use of LINGO optimization software.

Wang et al. [20] discussed the use of conflicting objectives in the design of a dynamic cellular manufacturing system. They solved the model using scatter search approach and compared the results obtained with the branch-and-bound and branch-and-cut of the CPLEX for different example problems. Jayakumar and Raju [21] developed a multi-period, non-linear mathematical cell formation model and solved it with LINGO commercial software for small and medium-sized problems. The problem got solved to optimality for the small-sized instances while for the medium-sized problems, solving the instances in a reasonable period of time was not possible. Their model encompasses several real-life parameters like alternate routings, operation sequences, duplicate machines, product mixes, product demands, batch sizes, processing times, and machine capacities. Deljoo et al. [22] claimed that previous research papers have substantial errors in applying GA to the cell formation problem. They improved the application of GA in solving a multi-period cell formation problem. Mahdavi et al. [23] presented a nonlinear mixed integer programming model for production planning of a cellular manufacturing system while considering flexibility in workforce management. Their model aims at minimizing the holding and backordering costs, inter-cell material handling cost, reconfiguration cost, as well as salary, hiring, and firing costs. Their model encompasses several design elements including operational time, alternative workers, duplicate machines, removing or adding machines to the system, machine capacity, hiring and firing of the workers, production volume of parts, inter-cell material handling, and reconfiguration of the cells. They used LINGO software to solve small-sized instances of the mathematical model. Javadian et al. [24] proposed a multi-objective dynamic cell formation problem whilst considering reconfigurability. Their objective function aims at minimizing different costs in the objective function including machine procurements, inter-cell and intra-cellular material handlings, back order, inventory holding, and subcontracting costs. They used a Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) for solving the mathematical model.

Rafiee et al. [25] developed an integrated cellular manufacturing system in which inventory lot sizing problem was integrated with the cell formation problem in a dynamic setting. They considered the reliability considerations of the machines as well as preventive and corrective maintenance in developing their model. They solved the model with the use of particle swarm optimization (PSO) algorithm to get near-to-optimal solutions for the large-sized instances. Saxena and Jain [26] developed a detailed mathematical model incorporating the reliability considerations of the machines with the cell formation problem. They investigated the effects of the machine breakdowns as well as the production time loss on the total cost. They solved the model with the use of CPLEX. Sharifi et al. [27] developed a mathematical model for designing a dynamic cellular manufacturing system. Their model aims at minimizing setup time in sequence-dependent manufacturing cells. They used a GA approach for solving the mathematical model. Saidi-Mehrabad et al. [28] proposed a mathematical model to integrate production planning and workers assignment in a cellular manufacturing system. Their model minimizes the costs of maintenance and overheads, system reconfiguration, backorder, inventory holding, training, and salaries. Fan and Feng [29], for the first time, developed a quasi-dynamic cellular manufacturing system. They solved the model using a GA. Majazi-Delfard [30] improved the material flow in a cellular manufacturing system in shorter distances by taking the quantity and average run length of the inter-cell and intra-cell movements into account. He solved the model with the use of SA embedded branch-and-cut algorithm. Sharifi et al. [31] developed a mixed-integer multi-period mathematical model for designing a dynamic cellular manufacturing system. They solved the model with the integration of a dynamic programming heuristic and GA. They compared the solution capability of their proposed integrated algorithm with the LINGO software and a GA-based heuristic. Results obtained showed the superiority of the integrated algorithm over the off-the-shelf software as well as the multi-period GA-based heuristic. Kia et al. [32] developed a mathematical model for designing a multi-floor cellular manufacturing system in a multi-period setting. Their objective function encompasses the minimization of different cost elements such as intra-cell and inter-cell material handling, inter-floor material handling, purchasing machines, machine processing, machine overhead, and machine relocation. They solved the model with the use of CPLEX to get exact solutions and a GA-based heuristic to get near-to-optimal solutions. Javadi et al. [33] developed a mathematical model for minimizing the inter-cell and intra-cell material handling of a cellular manufacturing system. They developed an electromagnetism-like embedded genetic algorithm for solving their model. Results obtained showed the superiority of the proposed algorithm over off-the-shelf software and GA. Niakan et al. [34] developed a multi-objective mathematical model for designing a cellular manufacturing system while considering social criteria such as number of job opportunities and potential hazards of the machines. They also developed a robust counterpart of the model. They solved the mathematical model with the use of NSGA II. Niakan et al. [35] developed a bi-objective mathematical model for the design of a dynamic cellular manufacturing. The first objective minimizes the summation of the production and workers costs while the second objective minimizes the total production wastes such as chemical materials, raw materials, and CO2 emissions. They solved the mathematical model with the combination of NSGA (II) algorithm and a multi-objective SA. Table 2-1 summarizes the related literature pertinent to dynamic cellular manufacturing systems.

Table 2-1 Summary of the literature review related to deterministic dynamic cellular manufacturing

Author	Year	Objective Function	Solution Approach	Inventory	Worker Element	Material Handling	Alternative Routings	Lot Splitting
Safaei and Tavakkoli-Moghaddam	2009	Configuration Costs	Branch and Bound, LINGO			Inter-cell Intra-cell		
Wang et al.	2009	Reconfigurability + Utilization + Inter-cell	Scatter Search					
Jayakumar and Raju	2010	Configuration Costs	LINGO			Inter-cell	✓	
Deljoo et al.	2010	Configuration Costs	GA			Inter-cell		
Mahdavi et al.	2011	Configuration Costs	LINGO	✓	✓	Inter-cell		
Javadian et al.	2011	Configuration + Cell Load Variation	NSGA II	✓		Inter-cell Intra-cell		
Rafiee et al.	2011	Configuration Cost	PSO			Inter-cell Intra-cell	✓	✓
Saxena and Jain	2011	Configuration Cost	LINGO			Inter-cell Intra-cell	✓	
Sharifi et al.	2012	Configuration Cost	GA, LINGO			Inter-cell		
Saidi-Mehrabad et al.	2013	Production Planning and Inventory Costs	LINGO	✓	✓	Inter-cell		
Fan and Feng	2013	Configuration + Worker Assignment	GA		✓	Inter-cell Intra-cell		
Majazi Delfard	2013	Configuration Cost	SA embedded Branch and Cut			Inter-cell Intra-cell		
Sharifi et al.	2014	Configuration Cost	DP, GA, LINGO			Inter-cell		
Kia et al.	2014	Configuration Cost	GA			Inter-cell Intra-cell Intra-floor		
Javadi et al.	2014	Configuration Cost	EM-GA			Inter-cell Intra-cell		
Niakan et al.	2015	Configuration Cost + Social Criteria	NSGA II		✓	Inter-cell Intra-cell	✓	
Niakan et al.	2016	Configuration Cost + Social Criteria	NSGA II-SA		✓	Inter-cell Intra-cell	✓	

Table 2-1 Continued

Author	Year	Solution Method	Inventory	Lot Splitting	Worker Element	Material Handling	Alternative Routings	Objective Function (Minimization)	Stochastic Parameters	Chance-Constrained	Closed-loop supply chain
Tavakkoli-Moghaddam et al.	2006	LINGO-SA				Inter-cell Intra-cell		Inter-cell + Intra-cell	Demand		
Tavakkoli-Moghaddam et al.	2007	LINGO				Inter-cell Intra-cell		Inter-cell + Intra-cell	Demand		
Saidi-Mehrabad and Ghezavati	2009	LINGO						RU + IM + SE	Processing Time & Arrival Time		
Jayakumar and Raju	2009										
Ghezavati and Saidi-Mehrabad	2010	GA + SA		✓		Inter-cell	✓	ET+SE+RU	Processing Time		
Arkat et al.	2011	LINGO		✓			✓	Configuration Cost	Breakdown Time	✓	
Ghezavati	2011	GA + SA	✓			Inter-cell Intra-cell		Production Planning and Inventory Costs	Demand and Processing Time		
Ghezavati and Saidi-Mehrabad	2011	GA + SA				Inter-cell		Maximizing probability of Machine Utilization	Processing Time and Arrival Time		
Fardis et al.	2013	CPLEX	✓			Inter-cell		IM + SE + RU + HP	Processing Time and Arrival Time	✓	
Eglimez et al.	2014	Arena Simulation Software			✓	Inter-cell		Maximizing Production Rate	Demand and Processing Time		
Jayakumar and Raju	2014	SA		✓		Inter-cell Intra-cell	✓	Configuration Cost	Product Mix		
Salarian et al.	2014	CPLEX				Inter-cell		Inter-cell	Processing Time and Arrival Time, Demand		
Fattahi et al.	2015	LINGO-GA-MPSO				Inter-cell		Maximizing Average Mean Waiting Time	Processing Time and Arrival Time		

2.3 Stochastic Cellular Manufacturing Systems

In this section a review of the literature is done corresponding to stochastic cellular manufacturing. We have investigated different papers regarding several features of stochastic cellular manufacturing systems such as objectives, problem-solving approaches, and material handlings including inter-cell and intra-cell movements. Tavakkoli-Moghaddam et al. [36] developed a nonlinear integer programing model considering both inter-cell and intra-cell material handling costs as well as stochastic demands. Their model determines the locations of each machine in the shop floor as well as location of each cell. A SA algorithm was developed to solve the model in a reasonable amount of computational time. To show the efficiency of the proposed solution method. They compared the results obtained from SA and LINGO software for the small-sized instances of the model. Tavakkoli-Moghaddam et al. [37] proposed a model with stochastic demands to minimize inter-cell and intra-cell material handling costs. Part demands were assumed to have normal distribution according to the data collected in the previous periods. They applied a branch-and-bound approach to solve the model for different confidence levels. Saidi-Mehrabad and Ghezavati [38] developed a mathematical model for designing a stochastic cellular manufacturing system operating in a queuing network. Their model aims at minimizing the summation of three cost types including (1) the idleness costs for machines, (2) total cost of sub-contracting for exceptional elements and (3) the cost of resource underutilization. They solved their model using LINGO optimization software. In a review paper, Jayakumar and Raju [39] investigated various aspects of designing deterministic and stochastic cellular manufacturing systems to provide possible directions for the future research. Ghezavati and Saidi-Mehrabad [40] developed a mathematical model for designing a stochastic cellular manufacturing system with uncertain processing time. They considered group scheduling problem to avoid having material handling activities. They solved the model an integrated solution approach which combines the simulated annealing and genetic algorithm. Arkat et al. [41] compared a chance-constrained stochastic cellular manufacturing mathematical model with a general cellular manufacturing model considering reliability of machines. They showed that using chance-constrained model yields lower total costs. Ghezavati [42] presented a stochastic mixed integer model to design a cellular manufacturing system under supply chain consideration where suppliers are required to operate exceptional products. He developed a hybrid metaheuristic method combing GA and SA to solve the mathematical model. Ghezavati and Saidi-Mehrabad [43] developed a mixed integer mathematical model for designing a stochastic cellular manufacturing considering continuous random parameters. They considered the processing time of the parts and inter-arrival of two consecutive parts in cells to be stochastic. They designed a queuing system in a cellular layout configuration in which each machine works as a server and each part is a customer where customers should be served. They solved their cell formation problem by optimizing the queuing system with the aim of maximizing the utilization of the server(s). They applied the combination of GA and SA to find near-to-optimal solutions. Fardis et al. [44] developed a non-linear mixed integer mathematical model for designing a stochastic cellular manufacturing system. They considered the inter-arrival time of the parts and the service rate of the machines to be stochastic and described by exponential distribution. Their mathematical model aimed at minimizing a set of costs including idleness cost of the machines, sub-contracting cost of the exceptional parts, non-utilizing machine cost, and holding cost of parts in the cells. Their mathematical model also features a chance-constrained where the waiting time of the parts behind each machine does not violate a predefined critical waiting time. They solved the model to optimality using an off-the-shelf software CPLEX. Egilmez et al. [45] proposed a stochastic worker assignment model considering stochastic processing time and stochastic demands. They developed a four-phased hierarchical method. In the first phase alternative configurations were developed with respect to a nonlinear stochastic model. In the second phase to convert the probabilistic demands into probabilistic capacity requirements, an Independent and Identically Distributed (IID) sampling and statistical analyses were implemented. Next, stochastic worker assignment were implemented and products were assigned into cells. Finally, individual worker assignments was performed. Jayakumar and Raju [46] presented a multi-objective single-period model considering uncertainty of the product mix. Due to the NP-hardness of the cell formation problem, they developed a SA algorithm to efficiently solve the mathematical model. Salarian et al. [47] designed a stochastic cellular manufacturing system where the demands, processing time, and inter-arrival of two consecutive part types were considered to be uncertain. Their model aims at optimizing the bottleneck of the system as well as minimizing the inter-cell material handling costs. Fattahi et al. [48] developed a stochastic mathematical model for designing a cellular manufacturing system. Their model aims at minimizing exceptional elements by maximizing waiting time of the parts in the queue behind of each machine type in each cell. They solved the model with the use of GA and PSO to get near-to-optimal solutions. Esmailnezhad et al. [49] presented a stochastic nonlinear model considering stochastic variables such as time between two successive arrival of the parts, processing time, and machine availability. They linearized the nonlinear model with the use of auxiliary variables. To efficiently solve the mathematical model, they developed a GA as well as a PSO to get near-to-optimal solutions. Ghezavati [50] presented a mathematical model for designing a cellular manufacturing integrated with the production planning problem where holding and backordering costs were uncertain. Their model aims at minimizing the expected holding and backordering costs as well as the subcontracting costs for exceptional elements.

Rabbani et al. [51] studied the manpower allocation and cell loading problem with the use of simulation where the part demands and processing time are stochastic and normally distributed. They considered the learning and training policies to allocate the workers in cells. Three scenarios of learning, training, and the combination of learning and training were considered in their model. They showed that enhancing the dexterity of the workers can result in the reduction of material handling costs and processing times of the parts on different machines. They also demonstrated that adopting encouraging policies (increasing salary) or punishment policies (decreasing salary) can improve the incentive of operators to serve the system better. Bootaki et al. [52] developed a mathematical model for designing a multi-objective stochastic cellular manufacturing system where the part-machine incidence matrix can vary over the different time horizons. They solved the model using a non-dominated sorted genetic algorithm II (NSGA-II). Zohrevand et al. [53] developed a bi-objective stochastic mathematical model for designing a dynamic cellular manufacturing system. The first objective of the model minimizes various cost elements including machine procurement, machine relocation, inter-cell moves, overtime utilization, worker hiring/laying-off, and worker moves between cells. The second objective also strives for maximizing the utilization of the workers. An integrated solution approach combining the TS and GA were applied to find the near-to-optimal solutions. Eglimez et al. [54] presented a non-linear stochastic mathematical model for designing a dynamic cellular manufacturing system. They proposed, for the first time, the use of stochastic genetic algorithm in solving the cell formation problem. Their proposed solution approach was able to reduce the solution time substantially. Mahootchi et al. [55] developed a two-stage stochastic model for designing a cellular manufacturing system considering multiple process routings and subcontracting of the part demands. They solved the model with the use of GAMS software. They also applied sample average approximation (SAA) method for different example problems. Golmohammadi et al. [56] designed a stochastic cellular manufacturing system where part demands are assumed to be stochastic. They solved the model to optimality with an off-the-shelf software GAMS. To find near-to-optimal solutions for the large-scale instances of the mathematical model, they developed a GA-based heuristic. Forghani and Fatemi Ghomi [57] developed a mathematical model for designing a cellular manufacturing considering queuing networks and multiple process routings. They applied a heuristic method to get near-to-optimal solutions. Table 2 summarizes the literature corresponding to stochastic cellular manufacturing systems.

Table 2-2 Summary of the literature review pertinent to stochastic cellular manufacturing

Author	**Year**	**Solution Method**	**Inventory**	**Lot Splitting**	**Worker Element**	**Material Handling**	**Alternative Routings**	**Objective Function (Minimization)**	**Stochastic Parameters**	**Chance-Constrained**	**Closed-loop supply chain**
Tavakkoli-Moghaddam et al.	2006	LINGO-SA				Inter-cell Intra-cell		Inter-cell + Intra-cell	Demand		
Tavakkoli-Moghaddam et al.	2007	LINGO				Inter-cell Intra-cell		Inter-cell + Intra-cell	Demand		
Saidi-Mehrabad and Ghezavati	2009	LINGO						RU + IM + SE	Processing Time & Arrival Time		
Jayakumar and Raju	2009										
Ghezavati and Saidi-Mehrabad	2010	GA + SA		✓		Inter-cell	✓	ET+SE+RU	Processing Time		
Arkat et al.	2011	LINGO		✓			✓	Configuration Cost	Breakdown Time	✓	
Ghezavati	2011	GA + SA	✓			Inter-cell Intra-cell		Production Planning and Inventory Costs	Demand and Processing Time		
Ghezavati and Saidi-Mehrabad	2011	GA + SA				Inter-cell		Maximizing probability of Machine Utilization	Processing Time and Arrival Time		
Fardis et al.	2013	CPLEX	✓			Inter-cell		IM + SE + RU + HP	Processing Time and Arrival Time	✓	
Eglimez et al.	2014	Arena Simulation Software			✓	Inter-cell		Maximizing Production Rate	Demand and Processing Time		
Jayakumar and Raju	2014	SA		✓		Inter-cell Intra-cell	✓	Configuration Cost	Product Mix		
Salarian et al.	2014	CPLEX				Inter-cell		Inter-cell	Processing Time and Arrival Time, Demand		
Fattahi et al.	2015	LINGO-GA-MPSO				Inter-cell		Maximizing Average Mean Waiting Time	Processing Time and Arrival Time		

Table 2-2 Continued

Author	Year	Solution Method	Inventory	Lot Splitting	Worker Element	Material Handling	Alternative Routings	Objective Function (Minimization)	Stochastic Parameters	Chance-Constrained	Closed-loop supply chain
Esmailnezhad et al.	2015	LINGO-GA-MPSO				Inter-cell		Maximizing Average Effective Arrival Rate	Processing Time and Arrival Time		
Ghezavati	2015	LINGO-GA				Inter-cell		Production Cost + SE	Holding, Back-Ordering, and Production Costs		
Rabbani et al.	2016	Any-Logic Software			✓	Inter-cell		Voids in the Task and Interest Matrix	Demand and Processing Time		

2.4 Remanufacturing and Hybrid Manufacturing-Remanufacturing Systems

In recent years, designing hybrid manufacturing-remanufacturing systems have become a topic of substantial interest due to the economic opportunities, social incentives, and environmental legislations. In addition to economic, social and environmental incentives, remanufacturing may provide companies with the benefits of having "green image". In this section, a review of relevant papers on remanufacturing systems and hybrid manufacturing-remanufacturing systems is presented. We have studied several aspects of hybrid manufacturing-remanufacturing such as objectives, problem-solving approaches, collection, disassembly, remanufacturing of the used products, incorporation of remanufacturing activities into new product manufacturing, and the nature of applied parameters including deterministic and stochastic. Laan et al. [58] investigated the production planning and inventory control aspects of the hybrid manufacturing-remanufacturing systems using push and pull control strategies. They compared the push and pull controlled systems with traditional systems without remanufacturing option. The results obtained revealed that total cost of the system tends to be lower in traditional manufacturing systems without remanufacturing option. However, total cost of the system might be lower in push and/or pull controlled systems using remanufacturing given that the uncertainties of the system are under control. Laan et al. [59] investigated the effect of lead-time duration and lead-time variability on the total expected costs of the hybrid manufacturing-remanufacturing systems using push and/or pull control strategies. A numerical study demonstrated that the variability in manufacturing lead-time has more significant influence on total expected costs of the system. Also, a larger remanufacturing lead-time and a larger variability in manufacturing lead-time may result in a cost decrease. Parkinson and Thompson [60] presented the accurate definitions of different processes in reverse logistics and remanufacturing including refurbishing, reconditioning, etc., because these processes were used with relatively the same meaning in publications. They also specified that remanufacturing operations can be implemented either by Original Equipment Manufacturer (OEM) or Third Part Remanufacturer (TRP), but it is common for having a collaboration between an OEM and a TPR. Inderfurth [61] investigated the effect of uncertainty in demand and quantity of returned products in a hybrid manufacturing-remanufacturing system. A stochastic dynamic programming approach was developed aims at optimal production, remanufacturing, and landfill decisions in a multi-period setting. The recovery ratio reduced with an increase in both quantity of returned products and demands. Sensitivity analyses demonstrated that decreasing the variability of returns and demands as well as improving the efficiency of recovery processes can improve the recovery rates.

Li et al. [62] studied the production planning and inventory control strategies of the hybrid manufacturing-remanufacturing system considering stochastic demands and stochastic returns of the used products. Their model aims at minimizing the total cost including remanufacturing costs, holding costs for returns and remanufactured products, as well as the backlog costs for the determination of optimal production lot sizes in a multi-period setting. Doh and Lee [63] proposed a mixed integer multi-period model for production planning of a remanufacturing system aims at maximizing the total profits. Their model encompasses decisions regarding the number of products to be disassembled, number of parts to be reprocessed, number of parts to be disposed, number of new parts to be purchased, and number of products to be reassembled. Wang et al. [64] studied the hybrid manufacturing-remanufacturing systems for the short life-cycle products. They considered stochastic demand and stochastic number of the returned products to calculate the effects of the quantity of the manufactured products as well as the ratio of the remanufactured products to the returned products on total costs of the system. Sensitivity analyses indicated that by setting optimal values of the number of manufactured products and the ratio of the number of remanufactured parts to the number of returned products, total cost of the system will be decreased significantly. Accordingly, mixed strategy using manufacturing, remanufacturing, and disposal at the same time results in a lower total cost of the system when manufacturing, remanufacturing, and disposal are used alternatively. Results obtained also showed that optimum values of the decision variables are more sensitive to product-process related parameters. Hasanov et al. [65] investigated a hybrid manufacturing-remanufacturing system where shortages in satisfying the demands for manufactured and remanufactured items are either fully or partly backordered. Kim et al. [66] investigated the effect of integrating disposal decisions in a hybrid manufacturing-remanufacturing system. Goodall et al. [67] presented a literature review on the improvements in tools and techniques to evaluate the viability of remanufacturing.

Chen and Abrishami [68] presented a mixed integer mathematical model aims at minimizing the total costs of a hybrid manufacturing-remanufacturing system. Their model encompasses decisions about the optimal quantities of the manufactured and remanufactured products to be produced and to be stored, returns to be acquired, to be disassembled, and to be stored in a multi-period setting. They assumed that the demands for remanufactured products are known and distinct from the demands for manufactured products. They also assumed both manufacturing and remanufacturing take place in the same facility by using the same limited resources. They developed a solution procedure based on Lagrangian-relaxation decomposition to efficiently solve the mathematical model in reasonable amounts of computational time. Baki et al. [69] proposed a multi-period mixed integer programing model to find the optimal lots of a remanufacturing system. They developed a heuristic using Wagner–Whithin approach to find the optimal lot sizes. Su and Xu [70] developed a mathematical model to minimize the remanufacturing costs considering uncertainty in the quality of the returned products. Guo and Ya [71] developed a stochastic programming model to determine the optimal manufacturing and remanufacturing lots considering minimum quality level of returns. They assumed that the quality of returns has exponential distribution. Obtained results revealed that it is promising to use higher remanufacturing cost to remanufacture the lower quality of recycled products to reduce the average total cost. Aljuneidi and Bulgak [72] investigated the combination of reconfigurable cellular manufacturing systems with hybrid manufacturing remanufacturing systems as an effort to design sustainable manufacturing systems. They developed a mixed integer mathematical model integrating a classical cell formation problem with configurability and production planning problem in a hybrid manufacturing remanufacturing environment. The overall objective function of the model was to minimize the total costs incorporating machine costs, manufacturing and remanufacturing costs, and costs related to returned products. Fang et al. [73] developed a mixed integer model to minimize the total costs of the system considering stochastic demands for both manufactured and remanufactured products. They assumed both manufacturing and remanufacturing use the same resources. They developed a solution procedure based on Lagrangian-relaxation decomposition to efficiently solve the mathematical model. Aljuneidi and Bulgak [74] developed a mathematical model for designing a cellular hybrid manufacturing-remanufacturing system considering the recycling of the end-of-life components. They also considered remanufacturing option for the end-of-life components as well as disposal option for components that cannot be economically recovered. They solved the model using CPLEX optimization software. Wang et al. [75] modeled the economic benefits of remanufacturing activities. They considered Bass diffusion model to show the diffusion dynamics of a new manufactured product in targeted markets. They evaluated the influence of diffusion dynamics of a product in the market on the volume of components reused in the single-generation life cycle of a product. Liu et al. [76] developed a mathematical model for designing a hybrid manufacturing-remanufacturing system considering resource depletion and environmental deterioration. They developed a mathematical model to minimize the total configuration cost of the manufacturing system and solved using the ant colony system algorithm with random sampling method (ACS-RSM). One of the major finding of their model was to show that the total cost of the system decrease intensely until to a certain point, when the quality of the returned products is high. When the quality of the returned products is equal or higher than 91%, the total cost of the system remains constant. Another major finding of their model was to demonstrate that increasing the lot sizes of the manufactured and remanufactured products has a substantial effect on increasing the total cost and the CPU time of their proposed solution methodology. In another research paper, Aljuneidi and Bulgak [77] developed a mathematical model for designing a sustainable cellular manufacturing enterprise. Their model aims at minimizing the carbon emissions and travel distances between each facility in the closed-loop supply chain. They solved the model with the use of CPLEX. Table 2-3 summarizes the literature relevant to remanufacturing and hybrid manufacturing-remanufacturing systems.

Table 2-3 Summary of the literature review pertinent to remanufacturing and hybrid manufacturing-remanufacturing systems

Author	Year	Main Work	Solution Approach
Laan et al.	1999	Investigation on production planning and inventory control of the hybrid manufacturing-remanufacturing systems using push and/or pull control strategies.	-
Laan et al.	1999	Investigation on the effect of lead-time duration and lead-time variability on total expected costs of the hybrid manufacturing-remanufacturing systems using push and/or pull control strategies.	-
Parkinson and Thompson	2003	Accurate definitions of different processes in reverse logistics and remanufacturing.	-
Inderfurth	2004	Investigation on the effects of uncertainty in demand and quantity of returned products.	
Li et al.		Production planning and inventory control strategies of the hybrid manufacturing-remanufacturing system considering stochastic demand and stochastic returns of the used products.	Dynamic Programming-based heuristics
Doh and Lee	2010	Designing a remanufacturing system aims at maximizing total profits.	CPLEX
Wang et al.	2012	Hybrid manufacturing-remanufacturing system for the short life-cycle products considering stochastic demand and stochastic returns to calculate the optimal quantity of the manufactured products and the effect(s) of the ratio of the remanufactured products to the returned products on total costs of the system.	-
Hasanov et al.	2012	Investigation a hybrid manufacturing-remanufacturing system where shortages in satisfying the demands for manufactured and remanufactured items are either fully or partly backordered.	Heuristic
Kim et al.	2013	Investigation on the effect of integrating disposal decisions in a hybrid manufacturing-remanufacturing system.	Wagner-Whitin Heuristic
Chen and Abrishami	2014	Decisions on the optimal quantities of the manufactured and remanufactured products to be produced and to be stored as well as decisions on optimal number of returned products to be acquired, disassembled, and stored.	Lagrangian-relaxation

Table 2-3 Continued

Author	Year	Main Work	Solution Approach
Su and Xu	2014	Minimizing the remanufacturing costs considering uncertainty in the quality of the returned products	-
Guo and Ya	2015	Optimal manufacturing and remanufacturing lots considering quality levels of returned products.	
Aljuneidi and Bulgak	2015	Optimal decisions on operational planning of the cellular manufacturing systems and tactical planning of the closed-loop supply chain considering work-force management.	CPLEX
Aljuneidi and Bulgak	2016	Optimal decisions on operational planning of the cellular manufacturing systems and tactical planning of the closed-loop supply chain in a hybrid manufacturing-remanufacturing system.	CPLEX
Wang et al.	2017	Bass diffusion model to show the diffusion dynamics of a new manufactured product in targeted markets.	-
Fang et al.	2017	Minimizing the total costs of the system considering stochastic demands for both manufactured and remanufactured products	Lagrangian-relaxation
Liu et al.	2018	Designing a hybrid manufacturing-remanufacturing system considering resource depletion and environmental deterioration.	ant colony system algorithm with random sampling method (ACS-RSM)
Aljuneidi and Bulgak	2019	Optimal decisions on strategic and operational planning of the cellular manufacturing systems and tactical planning of the closed-loop supply chain with cellular layout on the manufacturing side.	CPLEX

2.5 Closed-loop Supply Chains

Closed-loop supply chains have been designed in response to the needs of sustainable supply chains. Closed-loop supply chains basically covers two flows of materials where in addition to considering forward flow of materials from suppliers to end customers, flow of products back from customers to manufacturers are investigated. The major importance of closed-loop supply chains is attributed to environmental and societal pressures as well as profitability of recovery practices. There exists a vast amount of research papers corresponding to closed-loop supply chains and reverse logistics. Jayaraman et al. [78], as an early study, investigated the production planning problem of a manufacturing system as a part of a closed-loop supply chain. They developed a multi-period linear programming model for taking optimal decisions regarding the acquired, disassembled, remanufactured, and disposable returned products. They classified the quality levels of the returned products from poor to good ones. They applied their mathematical model on a case study from a cell phone manufacturer and they used CPLEX software to optimally solve their model. Fleischmann et al [79] designed a closed-loop supply chain where remanufacturing and disassembly centers were considered to be incapacitated in the reverse chain. Lu and Bostel [80] designed a hybrid manufacturing-remanufacturing work as a part of closed-loop supply chain. They solved the model to optimality using Lagrangian-relaxation method. Uster et al. [81] designed a closed-loop supply chain integrated with the facility location problem to locate the collection and remanufacturing facilities. Their model aimed at minimizing the summation of processing, transportation, and fixed location costs. They solved the model with the use of Benders-decomposition to optimality. Listes et al. [82] developed a two-stage stochastic mathematical model for designing a capacitated closed-loop supply chain considering stochastic demands and quality of the returned products. The procedure for implementing their network are as follows: Due to take-back legislation, original manufacturers must collect the used products from customers for either remanufacturing or appropriate disposal. All the collected products are sent to inspection/testing centers to be examined qualitatively and if necessary to be disassembled. To be qualified for remanufacturing, collected products must pass the quality checks, while products cannot pass the quality checks are going to be disposed. They solved the model using L-shaped method.

Salema et al. [83] developed a mixed programming model for designing a closed-loop supply chain considering uncertainty in products demands and quantity of the returned products. They solved the model with CPLEX. Demirel and Gökçen [84] developed a mixed integer mathematical model for designing a remanufacturing system work as a part of a closed-loop supply chain. They considered different operational and strategic decisions. Operational decisions include optimal production quantities and transportation of manufactured and remanufactured products. For the strategic decisions, optimal locations of disassembly, collection and distribution facilities were considered. They solved the model using GAMS. Min and Ko [85] developed a mixed-integer capacitated facility location model to find the optimal locations, quantity, and capacity of the warehouses and repair facilities in a closed-loop supply chain. They considered the third-party logistics companies for collecting the returned products in a more cost-effective mode. The results obtained revealed that the reduction in demands of the products, in declining part of the products life-cycle, reduces the possibility of product returns. That is, dynamic facility locations should be considered to let the firms modify their strategies against the demand variations. They assumed that existing warehouses can be utilized as overhaul centers with the possibility of expansion for both of them contributing to the economic design of the closed-loop supply chain. These authors developed a GA for efficiently solving the real-world instances of the proposed mathematical model in a less amount of computational time. Aras and Aksen [86] developed a model for the reverse collection of end-of-life products from customers, using a drop-off strategy, aims at profits maximization. Their model contains fixed customer zones and potential locations for collection centers as well as taking decision on the location of collection sites, amount of incentives, proportion of returned items, and the willingness of product holders to drop-off their old appliances. Product holders are supposed to get informed about the financial incentive values and closeness of a collection center to their residence before making an agreement for returns. The company offers financial incentives based on the quality levels of returned items. Due to the NP-hardness of the proposed mathematical model a TS-based heuristic was developed to solve the model in a reasonable amount of computational time. Pishvaee et al. [87] designed a multi-echelon closed-loop supply chain considering customers, collection/inspection facilities, and recovery/disposal centers. Due to the NP-hardness of the problem, they developed a SA algorithm for solving the large-sized instances. Their results from SA demonstrated the efficiency of their proposed solution method since the results from SA were close enough to obtained results from LINGO off-the-shelf software for the small-sized instances. Amin and Zhang [88] developed a single period mixed-integer mathematical model for designing a closed-loop supply chain. They considered a number of facilities in the network such as collection, repairing, disassembly, recycling, and disposal centers. They solved the model with the use of GAMS optimization software. Minner et al. [89] designed a closed-loop supply chain aims at minimizing the total costs where demands can be satisfied either by manufacturing new products or by remanufacturing used products. They used a linear model to quantify the relationship between acquisition costs and return rates. They developed a deterministic, dynamic, continuous-time model to find the optimal manufacturing-remanufacturing policies as well as the acquisition costs of the used products. Das and Chowdhury [90] integrated environmental pillar of the sustainability with a closed-loop supply chain. They considered different modular design schemes to accelerate manufacturing, remanufacturing, refurbishing, repairing, and disassembly resorting to new, reusable, or repairable components. Their model also encompasses finding optimal transportation and distribution routes to decrease the energy and detrimental emissions. They suggested using an incentive scheme for retailers to collect the end-of-life products from the customers and for customers to deliver their depreciated products.

Alumur et al. [91] designed a finite multi-period reverse logistic network considering facility location of collection and inspection centers, remanufacturing facilities, and recycling plants. Their model encompasses several important features such as a multi-period setting, capacity expansion of the facilities, reverse bill of materials, throughput at the facilities, variable operational costs, finite demands in the secondary market, and a profit-oriented objective function. They added reverse bill of material to consider the role of materials in remanufacturing activities. They solved their mathematical model using CPLEX software. Results obtained revealed that locating inspection centers and remanufacturers in the same sites is gainful as it reduces transportation costs between facilities. Özceylan and Paksoy [92] developed a multi-period mixed integer model to design a multi-commodity closed-loop supply chain including both forward and reverse flows. Their model determines the transportation amounts of the manufactured and remanufactured products and the location of different facilities in the loop as well as production planning of the manufacturing and remanufacturing centers. They also implemented different scenarios such as effect of changing demands, effect of changing collection rates, effect of changing capacities of plants and retailers, effect of changing reverse rates, effect of changing problem size to provide managerial insights for the readers. Diabat et al. [93] designed a reverse logistic network aims at minimizing the total reverse logistics costs including renting, inventory carrying, material handling, setup, and shipping costs. They developed a mixed integer non-linear model to determine the number and location of the collection centers as well as collection frequencies. They applied GA to efficiently solve the model in a reasonable amount of computational time. Alshamsi and Diabat [94] developed a mixed integer programming model for designing a reverse logistic network. Their model determines optimal selection of facilities as well as the capacities of inspection centers and remanufacturing facilities. Their model also determines the transportation options by analyzing outsourcing and in-house fleet transportation costs. Das et al. [95] presented a reverse logistic system considering modular design of the products for designing a recovery system at a lower cost. Their model encompasses several important processes in a reverse logistics design including collection of returned products, recovery of modules and proportion of the product mix at three different quality levels. These quality levels are corresponding to the use of new modules, a combination of new and recovered modules, and only recovered modules. Only one design using a mixture of new and recovered modules can produce a product. The main consideration of the problem is using retailers as the collectors of the returned products and considering third-party service providers as remanufacturers. Results revealed that limiting the amounts of investments can affect the decisions regarding the number and locations of facilities.

Soleimani et al. [96] designed a multi-period and multi-product closed-loop supply chain network considering stochastic demands as well as stochastic prices. A multi-criteria scenario-based solution approach based on the mean, standard deviation, and coefficient of variation was developed to efficiently solve the mathematical model. Shaw et al. [97] developed a mathematical model for designing a carbon footprint-based closed-loop supply chain considering carbon emissions and carbon trading. The carbon trading policy refers to the allowance of trading the carbon quota that is allocated to a firm. If a firm emits less than its prearranged carbon cap, then it sells the unused amount of carbon emission. Their model considered uncertainty for suppliers, plants, warehouses, and demands. Jeihoonian et al. [98] developed a mixed-integer mathematical model for designing a closed-loop supply chains of durable products with modular structure. They considered a sub-assembly tree where the number of each sub-assembly relies on the quality status of the returned products. They improved the solution capability of the Benders-decomposition with the use of several algorithmic enhancement to optimally solving their mathematical model. In another research paper, Jeihoonian et al. [99] proposed a two-stage stochastic mixed-integer mathematical model for designing a closed-loop supply chain considering uncertainty in the quality levels of the returned products using a Bernoulli distribution . They modelled the quality of the returned products as binary scenarios for each component in the reverse bill of material. They solved the mathematical model using an accelerated version of Benders-decomposition. Shu et al. [100] investigated the trade-off between incentives of the customers to buy remanufactured products with the carbon tax amounts in a closed-loop supply chain. Accordingly, customers tend to buy more remanufactured products when the carbon taxes is low. In order to regulate the market, they developed a mathematical model considering government subsides. Table 2-4 summarizes the related literature with the closed-loop supply chains.

Table 2-4 Summary of the literature review pertinent to closed-loop supply chains

Author	Year	Location decisions for reverse practices					Multi-period	Multi-product	Facility capacity	Second market	Uncertainty	Acquisition	Production Planning	Solution Approach
		CC	RCC	RMC	DAC	DPC								
Jayaraman et al.	1999	✓		✓				✓	✓					GAMS
Fleischmann et al.	2001	✓		✓										CPLEX
Lu and Bostel	2007	✓		✓		✓							✓	Lagrangian-Relaxation
Uster et al.	2007	✓		✓				✓						Benders-Decomposition
Listes et al.	2007	✓		✓					✓		D,QR	✓		L-Shaped Method
Salema et al.	2007	✓		✓				✓	✓		D,QR			CPLEX
Demirel and Gökçen	2008	✓		✓	✓	✓		✓	✓			✓		CPLEX
Min and Ko	2008	✓		✓			✓	✓	✓					Genetic Algorithm
Aras and Asken	2008	✓		✓								✓		Heuristic
Pishvaee et al.	2010	✓		✓		✓								LINGO, Simulated-Annealing
Amin and Zhang	2012	✓	✓		✓	✓		✓	✓					GAMS
Minner et al.	2012											✓		Analytical
Das and Chowdhouri	2012	✓		✓		✓		✓			D		✓	LINGO
Alumur et al.	2012		✓	✓	✓		✓	✓	✓					CPLEX
Ozceylan and Paksoy	2013	✓	✓	✓	✓	✓	✓	✓	✓					GAMS
Diabat	2013	✓		✓	✓	✓			✓					GA
Alshamsi and Diabat	2015	✓	✓	✓	✓	✓	✓	✓	✓	✓				CPLEX
Das et al.	2015	✓		✓		✓		✓						Pareto, Goal Programming
Soleimani et al.	2016	✓		✓	✓		✓	✓						CPLEX
Jeihoonian et al.	2016	✓	✓	✓	✓	✓		✓	✓	✓				CPLEX, Accelerated Benders-Decomposition

Table 2-4 Continued

Author	Year	Location decisions for reverse practices					Multi-period	Multi-product	Facility capacity	Second market	Uncertainty	Acquisition	Production Planning	Solution Approach
		CC	RCC	RMC	DAC	DPC								
Jeihoonian et al.	2017	✓	✓	✓	✓	✓		✓	✓	✓	QR			CPLEX, L-Shaped Method

2.6 Findings in the Literature Review

In this chapter, a detailed study of the literature is done regarding the design perspectives of the sustainable manufacturing enterprise. Following conclusions can be drawn from the review study of this chapter:

1. Designing sustainable manufacturing systems has received increasing attentions in recent years. Designing sustainable supply chains is an eminent research topic in general, although designing sustainable manufacturing systems and sustainable manufacturing enterprises are in their infancy era.
2. In view of the increasing attentions towards sustainability of the manufacturing systems with the use of cellular manufacturing systems, it is important to increase the efficiency and reliability of the manufacturing systems with the concepts such as alternative process routings, contingency process routings, subcontracting to satisfy the demands of the customers on-time without having back-ordering or lost-sales.
3. To design a sustainable manufacturing enterprise, applying the queuing theory in the manufacturing aspects of the mathematical model can highly be advantageous for optimizing the manufacturing system. Also, the use of chance-constrained mathematical models embedded queuing theory can highly boost the efficiency of the mathematical models.
4. Resorting to two-stage or multi-stage stochastic programming approaches in designing sustainable manufacturing enterprise has not been done in the literature. In using stochastic programming, value of stochastic solution (VSS) allows us to obtain the goodness of the expected solution value when the expected values are replaced by the random values for the input variables.

5. Cellular manufacturing systems, due to mass customization, and hybrid manufacturing-remanufacturing systems, due to their benefits in improving the sustainability pillars such as economic, societal, and environmental, can be used in the manufacturing aspect of the sustainable manufacturing enterprises.
6. The combination of cellular manufacturing layouts with remanufacturing systems and/or hybrid remanufacturing-remanufacturing systems to build the more efficient sustainable manufacturing systems is still in its infancy era.
7. Finally, each manufacturing system should work as a part of a sustainable closed-loop supply chain for building a sustainable manufacturing enterprise. This research direction is also in its infancy era corresponding to the review of the literature in this chapter.

Chapter 3 A mathematical model for designing a sustainable cellular manufacturing systems with Remanufacturing Recovery Option

3.1 Introduction

In this chapter, design optimization of a cellular manufacturing system as a part of a closed-loop supply chain is investigated to build a sustainable manufacturing enterprise. According to Figure 1, closed-loop supply chain encompasses both forward and reverse flows from the remanufacturing facility to the customers and from customers back to the remanufacturing facility. In the forward chain, returned products are remanufactured to fulfil the demands of customers. On the other hand, in the reverse chain, returned products are collected from the customer zones to be inspected and tested. In the disassembly center, returned products are pulled apart to separate the remanufacturable components. High-quality components are shipped to remanufacturing centers in which process of restoring returned products to "like-new" condition is performed. Low-quality components are going to be disposed. Remanufacturing usually encompasses several activities such as disassembly, cleaning, repairing, reassembly, and refurbishing. Recognizing the suitable manufacturing layout can highly increase the efficiency of manufacturing processes which leads to the design of a sustainable manufacturing systems. To achieve sustainability in manufacturing systems, cellular manufacturing layout is highly recommended [105]. The proposed model in this chapter considers several manufacturing attributes such as multi-period production settings, reconfigurable layouts of the system, outsourcing, machine duplication which refers to multiple units of identical machines, machine acquisition and machine capacity. There are several parameters pertaining to the reverse supply chain activities including acquisition and disassembly of the returned products, remanufacturing of parts having high quality, and disposal of the returned products that cannot be economically recovered. Figure 3-1 represents the material flow of the proposed sustainable cellular remanufacturing system. The overall objective function of the model is to minimize 4 sets of costs including (1) machine costs: maintenance and overhead costs, relocation cost of the machines, machine procurements, and machine operating cost, (2) inter-cell material handling cost, (3) remanufacturing cost of the returned products, and (4) costs associated with the returned products such as acquisition, disassembly, inventory holding, and disposal costs of the returned products. A mixed integer-linear programming (MILP) model for solving the above-described problem is formulated. The rest of the section presents the model assumptions, parameters, decision variables, formulation, as well as a detailed description of the proposed mathematical model and its linearization.

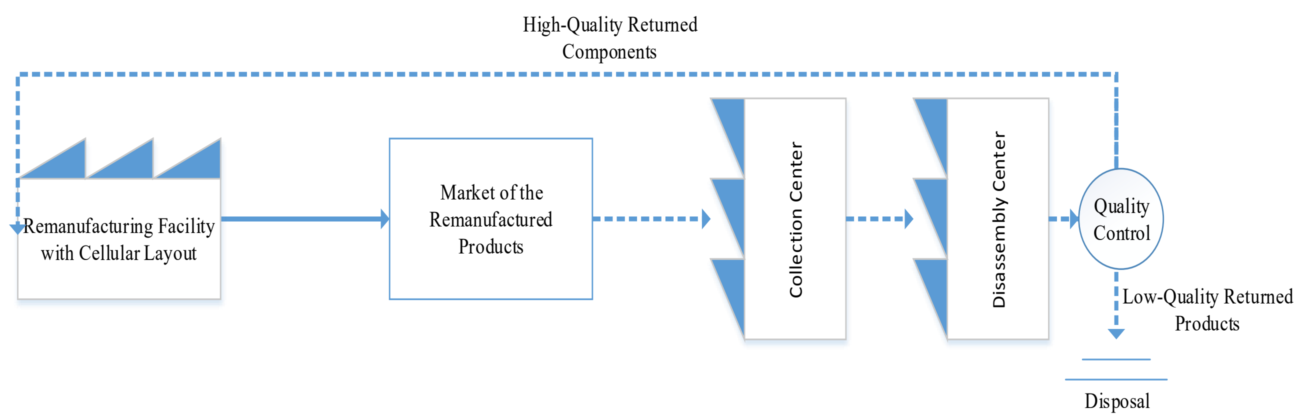

Figure 3-1 *Material flow diagram for the proposed cellular remanufacturing system*

3.2 Model Assumptions

When formulating the proposed mathematical model, several specific assumptions have been taken into account as follows:

- Predefined number of cells and the number is constant for each time period;

- The demand of each type of part is deterministic and known in advance in each time period;
- Each machine type has a limited capacity expressed in hours during each time period;
- Reconfiguration involves the addition and removal of machines to the cells and relocation from one cell to another in different time periods at the beginning of each time period;
- Machine maintenance and overhead costs are known and constant in each time period;
- Machine maintenance and overhead costs are considered for each machine in each cell and period regardless that the machine is active or idle;
- The demand for each part type in each time period can be fulfilled by internal productions as well as inventories that can be carried over from the previous time periods.
- Routing flexibility of parts are not considered.
- Each cell has a limited capacity. Lower and upper size limits of the cells are known in advance.
- There is an unlimited source of returned products.

3.2.1 Model parameters and decision variables

The notations used in the model are presented below followed by the objective function and set of constraints.

Problem Sets:

I: Index set of part types

M: Index set of machine types

C: Index set of cells

T: Index set of time periods

J: Index set of returned products

Parameters

D_{it}	Demand of product i in time period t
ξ_i^{inter}	Intercellular movement cost of part i
ψ_{im}	Part-Machine Incidence Matrix (If machine m processes part type i)
ρ_{im}	Processing time of part i on machine m
π_{mt}	Time capacity of machine m in time period t
α_c	Lower size limit of the cells
β_c	Upper size limit of the cells
R_m	Installation cost of machine m

K_m	Removal cost of machine m
M^{∞}	A large positive and integer number
H_{it}	Holding/Carrying cost of part type i in time period t
S_i	Subcontracting cost of part i
A_{mt}	Quantity of machine type m available at time period t
η_m	Machine maintenance and overhead costs
ω_m	Machine investment cost
γ_m	Operating cost of machine type m
E_i	Production cost per part type i
σ_{jt}	Unit cost to acquire returned product j in time period t
Φ_{jt}	Setup cost for disassembling returned product j in time period t
∇_{jt}	Unit cost to disassemble returned product j in time period t

β_{jt}	Unit inventory cost for returned product j in time period t
U_i	Average recovering rate of part i from all returned products j
V_{ij}	Number of part i contained in product j
κ_j	Disposal cost of returned product j

Decision Variables

N_{mct}	Number of type m machines present in cell c at the beginning of time period t
Y_{mct}^{+}	Number of type m machines added in cell c at the beginning of time period t
Y_{mct}^{-}	Number of type m machines removed from cell c at the beginning of time period t
ζ_{mt}	Number of machines of type m procured at time t
$\hat{A}_{mt}$	Quantity of machine type m available at time period t after accounting for machines that have been procured

Q_{it}	Number of part inventory of type i kept in time period t and carried over to period (t + 1)
X_{it}	Production volume of part type i to be produced in time period t
O_{it}	Quantity of part type i to be outsourced in time period t
τ_{ict}	= 1, if part type i is processed in cell c in period t. = 0, otherwise
Z_{imct}	= 1, if part type i is to be processed on machine type m in cell c in period t. = 0, otherwise.
d_{jt}	Number of returned product j to be disassembled in time period t
r_{jt}	Number of returned product j to be acquired in time period t
f_{jt}	Number of returned product j in the inventory at the end of time period t

3.2.2 Model formulation and description

Objective Function

Minimize

The objective function and constraints of the model are as follows:

$$\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{m=1}^{M} N_{mct} * \eta_m \tag{1.1}$$

$$+ \sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{m=1}^{M} R_m * Y_{mct}^{+} \tag{1.2}$$

$$+ \sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{m=1}^{M} K_m * Y_{mct}^{-} \tag{1.3}$$

$$+ \sum_{t=1}^{T}\sum_{i=1}^{I} Q_{it} * H_{it} \tag{1.4}$$

$$+ \sum_{t=1}^{T}\sum_{i=1}^{I}\left[\left(\sum_{c=1}^{C} \tau_{ict}\right) - 1\right] * \xi_i^{inter} * X_{it} \tag{1.5}$$

$$+ \sum_{t=1}^{T}\sum_{i=1}^{I} X_{it} * E_i \tag{1.6}$$

$$+ \sum_{t=1}^{T}\sum_{m=1}^{M} \zeta_{mt} * \omega_m \tag{1.7}$$

$$+ \sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{c=1}^{C} Z_{imct} * X_{it} * t_{im} * \gamma_m \tag{1.8}$$

$$+ \sum_{t=1}^{T}\sum_{j=1}^{J} \sigma_{jt} * r_{jt} \tag{1.9}$$

$$+ \sum_{t=1}^{T}\sum_{j=1}^{J} \Phi_{jt} * \delta_{jt} \tag{1.10}$$

$$+ \sum_{t=1}^{T}\sum_{j=1}^{J} \nabla_{jt} * d_{jt} \tag{1.11}$$

$$+ \sum_{t=1}^{T}\sum_{j=1}^{J} \beta_{jt} * f_{jt} \tag{1.12}$$

$$+ \sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{j=1}^{J} (1 - U_i) * \kappa_j * V_{ij} * d_{jt} \tag{1.13}$$

$$+ \sum_{t=1}^{I} \sum_{i=1}^{I} S_i * O_{it} \tag{1.14}$$

<u>Subject to:</u>

$$\mathrm{Q}_{\mathrm{it-1}} + \mathrm{X}_{\mathrm{it}} - \mathrm{Q}_{\mathrm{it}} = \mathrm{D}_{\mathrm{it}};\ \forall\ (\mathrm{i, t}) \tag{2}$$

$$\tau_{\mathrm{ict}} = \min\ (1, \textstyle\sum_{\mathrm{m=1}}^{\mathrm{M}} \mathrm{Z}_{\mathrm{imct}});\ \forall\ (\mathrm{i, c, t}) \tag{3}$$

$$\sum_{c=1}^{C} Z_{imct} \leq \psi_{\mathrm{im}};\ \forall\ (\mathrm{i, m, t}) \tag{4}$$

$$\mathrm{N}_{\mathrm{mct}} = \mathrm{N}_{\mathrm{mct-1}} + \mathrm{Y}_{\mathrm{mct}}^{+} - \mathrm{Y}_{\mathrm{mct}}^{-};\ \forall\ (\mathrm{m, c, t}) \tag{5}$$

$$\sum_{\mathrm{m=1}}^{\mathrm{M}} \mathrm{N}_{\mathrm{mct}} \geq \alpha_c;\ \forall\ (\mathrm{c, t}) \tag{6}$$

$$\sum_{\mathrm{m=1}}^{\mathrm{M}} \mathrm{N}_{\mathrm{mct}} \leq \beta_c;\ \forall\ (\mathrm{c, t}) \tag{7}$$

$$\sum_{\mathrm{i=1}}^{\mathrm{I}} \mathrm{Z}_{\mathrm{imct}}\ \rho_{\mathrm{im}}\ \mathrm{X}_{\mathrm{it}} \leq \mathrm{N}_{\mathrm{mct}}\ \ \pi_{\mathrm{mt}};\ \forall\ (\mathrm{m, c, t}) \tag{8}$$

$$\sum_{\mathrm{c=1}}^{\mathrm{C}} \sum_{\mathrm{m=1}}^{\mathrm{M}} \mathrm{Z}_{\mathrm{imct}} \leq M^{\infty}\ \mathrm{X}_{\mathrm{it}};\ \forall\ (\mathrm{i, t}) \tag{9}$$

$$\widehat{\mathrm{A}}_{\mathrm{m(t=1)}} = \mathrm{A}_{\mathrm{m(t=1)}} + \zeta_{\mathrm{m(t=1)}};\ \forall\ (\mathrm{m}) \tag{10}$$

$$\widehat{\mathrm{A}}_{\mathrm{m(t+1)}} = \widehat{\mathrm{A}}_{\mathrm{mt}} + \zeta_{\mathrm{m(t+1)}};\ \forall\ (\mathrm{m}) \tag{11}$$

$$\sum_{\mathrm{c=1}}^{\mathrm{C}} \mathrm{N}_{\mathrm{mct}} = \widehat{\mathrm{A}}_{\mathrm{mt}};\ \forall\ (\mathrm{m, t}) \tag{12}$$

$$\mathrm{f}_{\mathrm{jt}} + \mathrm{d}_{\mathrm{jt}} - \mathrm{f}_{\mathrm{jt-1}} = \mathrm{r}_{\mathrm{jt}};\ \forall\ (\mathrm{j, t}) \tag{13}$$

$$\mathrm{d}_{\mathrm{jt}} \leq M^{\infty}\ \delta_{\mathrm{jt}};\ \forall\ (\mathrm{j, t}) \tag{14}$$

$$\mathrm{X}_{\mathrm{it}} \leq \mathrm{U}_{\mathrm{i}} \sum_{\mathrm{j=1}}^{\mathrm{J}} \mathrm{V}_{\mathrm{ij}}\ \mathrm{d}_{\mathrm{jt}};\ \forall\ (\mathrm{i, t}) \tag{15}$$

$\sum_{i=1}^{I} Z_{imct} \le M^{\infty} N_{mct}; \forall (m, c, t)$ (16)

$N_{mct}, Y^{+}_{mct}, Y^{-}_{mct} \ge 0$ and integer; $\forall$ (m, c, t) (17)

$Q_{it}, X_{it} \ge 0$; $\forall$ (i, t) and integer (18)

$\zeta_{mt}, \widehat{A}_{mt} \ge 0$; $\forall$ (m, t) and integer (19)

$\tau_{ict} \in \{0, 1\}$; $\forall$ (i, c, t) (20)

$Z_{imct} \in \{0, 1\}$; $\forall$ (i, m, c, t) (21)

Model objective Function: The objective function of the model encompasses several cost terms. The first term (1.1) shows the maintenance and overhead costs of the machines. The second term (1.2) demonstrates the cost of machines installations while the third term (1.3) represents the cost of machines removals. The fourth term (1.4) shows the inventory carrying cost of the parts. The fifth term (1.5) represents the cost of intercellular movements of the parts between cells. The sixth term (1.6) addresses the production cost of the remanufactured components. The seventh term (1.7) represents machines investment cost. The eighth term (1.8) shows machines operating cost. The ninth term (1.9) represents acquiring cost of the returned products. The tenth term (1.10) represents the setup cost for disassembling operations. Eleventh term (1.11) addresses the disassembling cost of the returned products. The twelfth term (1.12) shows the inventory holding cost for returned products. Term thirteenth term (1.13) addresses the disposal cost of the returned products and the last term, term number fourteen (1.14) demonstrates outsourcing cost in satisfying the part demands. Costs in the objective function can be classified into four major categories including machines costs, material handling costs, remanufacturing costs of the returned products and costs corresponding to returned products such as acquisition, holding, disassembling setups, and disassembling activities that should be minimized.

Model Constraints: The objective function of the model is subjected to constraints as follows: Constraint (2) demonstrates that demands for part type i in each time period can be fulfilled by producing remanufactured products as well as accounting for the inventory carried over from previous time period subtracting the inventory of the current time period. Constraint (3) is pertinent to intercellular movements of the parts stating that if part type i is processed in cell c in each time period. Constraint (4) is to ensure that each part is assigned to appropriate machines in all the cells with respect to part-machine incidence matrix (MCIM). Part-machine incidence matrix declares that part i is processed with the use of machine m. Constraint (5) demonstrates the number of machines of type m at the beginning of each time period is equal to number of machines in the previous time period considering installations and removals of machines of type m in cell c at the beginning of each time period t. The size of the cells is user-defined through Constraints (6) and (7). Constraint (6) states that the number of machines assignments of each type should be greater than the lower size limit of the cells. Constraint (7) states that the number of machines assignments of each type should be greater than the lower size limit of the cells. Constraint (8) ensures that the capacity of machines would not be exceeded. Constraint (9) guaranties that when the system does not produce anything ($x_{it} = 0$), there are no assignments of machines or cells to different part types. Constraint (10) is relevant to the availability of machines for time period 1 taking into consideration machine procurements option. The total number of machines of each type available in the system is equal to the machine availability before machine procurements in addition to the number of machines acquired in the first time-period. Constraint (11) indicates that machine availabilities for the subsequent time periods excluding time period 1 can be recorded. The number of machines procurements in the current time period along with the number of machines that have been acquired in all the preceding time periods demonstrates total available machines in the system. Constraint (12) declares that total number of machines in each cell should not exceed the total number of available machines. Constraint (13) indicates that the total number of returned products to be acquired can be calculated through the summation of total number of returned products to be kept in inventory for the current time period as well as total number of returned products to be disassembled for the current time period subtracting the amounts of inventory carried over from the previous time period. Constraint (14) indicates a logical constraint for disassembling activities. Constraint (15) encompasses the bill of materials (BOM) and the quality levels of the returned products for calculating the quantity of parts acquired from returned products. BOM refers to the number of part i contained in the returned product j. Constraint (16) shows that Z_{imct} which determines the production routes of a part i with the use of machine m in cell c in time period t could be zero unless the same machine type is already assigned to cell c at the beginning of time period t. Constraint (17), Constraint (18), Constraint (19), Constraint (20), and Constraint (21) specify the logical binary and non-negativity integer requirements on the decision variables.

3.2.3 Linearizing the Objective Function

The objective function is a non-linear function due to the non-linear terms (1.5) and (1.8) as well as constraints 3 and 8. To transform these non-linear terms to linear ones, the following new variables are defined by Mahdavi et al. [23] as follows:

$F_{ict} = \tau_{ict} * X_{it}$

$W_{imct} = Z_{imct} * X_{it}$

By considering these equations, following constraints must be added to the model:

$F_{ict} \geq X_{it} - M\ (1 - \tau_{ict}); \forall\ (i, c, t)$ (22)

$F_{ict} \leq M\ (\tau_{ict}); \forall\ (i, c, t)$ (23)

$F_{ict} \leq X_{it}; \forall\ (i, c, t)$ (24)

$W_{imct} \geq X_{it} + M\ (1 - Z_{imct}); \forall\ (i, m, c, t)$ (25)

$W_{imct} \leq M\ Z_{imct}; \forall\ (i, m, c, t)$ (26)

$W_{imct} \leq X_{it}; \forall\ (i, m, c, t)$ (27)

$F_{ict}, W_{imct} \geq 0$ (28)

Also, to linearize the proposed model, constraint (3) should be replaced by these two constraints:

$\sum_{m=1}^{M} Z_{imct} \leq M\ \tau_{ict}; \forall\ (i, c, t)$ (29)

$\sum_{m=1}^{M} Z_{imct} \geq \tau_{ict}; \forall\ (i, c, t)$ (30)

Therefore, the objective function of the integer programming model has linear terms only. All the constraints in the proposed model are also linear. The number of variables and number of constraints in the proposed models are presented in Tables 3-1 and 3-2, respectively, based on the indices of the variables in the proposed model.

Table 3-1 Number of decision variables in the linearized model

Name of variables	Nature of variable	Variable count	Name of variables	Nature of variable	Variable count
N_{mct}	General Integer	M×C×T	X_{it}	General Integer	I×T
Y_{mct}^{+}	General Integer	M×C×T	τ_{ict}	Binary	I×C×T
Y_{mct}^{-}	General Integer	M×C×T	F_{ict}	General Integer	I×C×T
ζ_{mt}	General Integer	M×T	Z_{imct}	Binary	I×M×C×T
$\hat{A}_{mt}$	General Integer	M×T	d_{jt}	General Integer	J×T
Q_{it}	General Integer	I×T	r_{jt}	General Integer	J×T
f_{jt}	General Integer	J×T	δ_{jt}	General Integer	J×T
W_{imct}	General Integer	I×M×C×T			
Total: 3×(M×C×T) + 2×(I×C×T) + 2×(I×M×C×T) + 4×(J×T) + 2×(I×T) + 2×(M×T)					

Table 3-2 Number of constraints in the linearized model

Equation number	Total count	Equation number	Total count
2	I×T	14	J×T
3	I×C×T	15	J×T
4	I×M×T	16	M×C×T
5	M×C×T	22	I×C×T
6	C×T	23	I×C×T
7	C×T	24	I×C×T
8	M×C×T	25	I×M×C×T
9	I×T	26	I×M×C×T
10	1×M	27	I×M×C×T
11	M×T	29	I×C×T
12	M×T	30	I×C×T
13	J×T		
Total: 2×(I×T) + 4×(I×C×T) + 1×(I×M×T) + 3×(M×C×T) + 2×(C×T) + (1×M) + 2×(M×T) + 3×(J×T) + 3×(I×M×C×T)			

3.3 Numerical Example

To validate and verify of the proposed model, a number of example problems are solved with the use of IBM ILOG CPLEX Optimization Studio 12.7/OPL a commercially available optimization software. The data set used is based on the data used by Mahdavi et al. [23] and Chen and Abrishami [68]. Unknown parameters were extracted by cross-referencing between the data sets containing them to be incorporated inside the other data sets missing that information. For illustration purposes, a detailed discussion for the input data and computational results of one example problem (Example 1) is also presented. Since, other test problems are similar to Example 1, only summarized results are presented to further demonstrate the design issues addressed with the proposed mathematical model. All of the computational experiments are performed on Intel® Core™2.67 GHz workstation, with the problems being solved using IBM ILOG CPLEX Optimization Studio 12.7/OPL. Table 3-3 demonstrates different scenario examples of the proposed model. Elapsed time and optimality gaps (difference between current solution and best bound on optimal solution) are also shown in Table 3-3. Accordingly, CPLEX is not able to solve the last test problem namely problem scenario 7 which is a large-scale instance after 14,422 seconds with 0.06% optimality gap. After running the optimization software for 14,422 seconds the search was stopped due to the memory limitations. Therefore, branch and bound and branch and cut algorithms of the CPLEX are not able to produce good equality solutions within reasonable computational time for the largest instance of the proposed model considered in this article. Problem scenario 6 which is also a large-scale instance is solved to optimality after 298.29 seconds. Table 3-3 represents all the other test problems namely problem scenarios 1 to 6 of the proposed model have been solved to optimality and the computational times increase as the problem size grows from small-scale instances to medium ones in terms of the number of variables and constraints.

Table 3-3 Different problem scenario of the proposed model

Problem scenario	Classification	Number of parts	Number of machines	Number of cells	Number of time periods	Number of returned products	Number of variables	Number of constraints	Time elapsed (Second)	Optimality gap (%)
1	Small-Scale	1	2	2	2	3	84	108	0.65	0.00
2	Small-Scale	1	6	2	2	3	260	265	0.95	0.00
3	Medium-Scale	4	3	2	2	3	340	216	1.26	0.00
4	Medium-Scale	4	3	3	2	3	298	474	9.07	0.00
5	Medium-Scale	4	3	2	3	3	324	510	4.55	0.02
6	Large-Scale	4	4	2	5	3	660	1025	298.29	0.02
7	Large-Scale	4	2	4	3	3	432	717	14422	0.06*

*Search was stopped due to memory limitations

3.3.1 Example 1

In solving Example 1, 4 parts, 3 machines, 3 cells, 2 time periods, and 3 types of returned products are considered. The input data of this example are presented in Tables 3-4 – 3-8. Table 3-4 contains costs pertaining to different machine types as well as the capacity of each machine. Table 3-4 also demonstrates the number of machines of each type available in the system in the first time period which indicates the existing manufacturing layout is being reconfigured from a cellular manufacturing layout. If the number of machines available in the system is zero in the first time period, it reveals that a cellular manufacturing system is being reconfigured from no existing manufacturing layouts. Table 3-5 demonstrates costs related to returned products including disassembly, acquisition, inventory holding, and setup for disassembly. Table 3-6 represents the costs associated with different part types such as disposition, outsourcing, inventory carrying, inter-cell material handling, recovery rates as well as production costs per unit. Demands for remanufactured products are given in Table 8 for two consecutive time periods. In table 3-6, outsourcing cost has been generated randomly in the range of (250, 1000). Table 3-7 shows the part-machine incidence matrix. It represents if each part type needs any machines from the set of machine types. The numbers of components contained in different returned products are shown in Table 3-8. For example, there are 8 parts of type 4 contained in returned product 3.

Table 3-4 Machines' information

Machine		Cost					Capacity	
	Available Machines (A_m)	Operating	Overhead	Procurement	removal	Installations	T_1	T_2
1	2	18	400	4000	140	550	30	30
2	3	16	410	2000	130	530	30	30
3	1	14	430	2000	150	560	30	40

Table 3-5 Costs related to returned products

Returned Products	Cost				
	Time Period	Disassembly	Acquisition	Inventory Holding	Setup
1	1	30	25	40	20
1	1	35	15	40	30
2	2	25	35	50	25
2	2	30	20	50	20
3	3	20	25	30	22
3	3	18	28	30	33

Table 3-6 Parts' Information

Part		Cost					Demand	
	Outsourcing	Disposition	Inventory	Production	Inter-cell	Recovering Rate	T_1	T_2
1	580	200	4	20	11	0.5	0	1550
2	660	250	6	21	9	0.5	1700	500
3	513	220	8	23	8	0.6	900	600
4	642	300	10	20	10	0.2	1000	900

Table 3-7 Part-Machine Incidence Matrix

Parts/Machines	1	2	3
1	1	1	1
2	1	1	0
3	1	0	1
4	0	1	1

Table 3-8 Number of parts I in Returned Product J

Parts/Returned Products	1	2	3
1	10	10	8
2	12	12	10
3	15	11	3
4	13	12	8

3.3.2 Solution of Example 1

Production route of each part type in terms of machines and cells in each period is given in Table 3-9. Table 3-9 demonstrates the single process routing of all the part types. For example, part type 1 is going to be processed on machines 1, 2, and 3 in cell 2 during the second time period. Results pertaining to assignments of machines at the beginning of each time period are shown in Figure 3-2. For instance, 2 machines of type 1 is assigned to cell 3 at the beginning of period 2. Number of returned products to be acquired in each time period is presented in Table 3-10. Accordingly, 416 returned products of type 2 need to be acquired for the first time period while 375 returned products of the same type need to be acquired for the second time period. The number of returned products to be disassembled is completely equivalent with the number of returned products to be acquired for the same and subsequent time periods. Therefore, 416 returned products of type 2 are disassembled for the first time period while 375 of the same type are disassembled for the second period. The inventory levels of the returned products are zero for all types in all the time periods. Example 1 is solved apart from outsourcing option in satisfying the part demands. The effect of outsourcing option will be investigated in section 3.3.3.

Table 3-9 Production Route of Part I Resorting to Machine M in Cell C in Time Period T

Part (I)	Machine (M)	Cell (C)	Time Period (T)
1	1	1	1
1	1	2	2
1	2	1	1
1	2	2	2
1	3	1	1
1	3	2	2
2	1	1	2
2	1	2	1
2	2	1	2
2	2	2	1
3	1	3	1
3	1	3	2
3	3	3	1
3	3	3	2
4	2	1	1
4	2	2	2
4	3	1	1
4	3	2	2

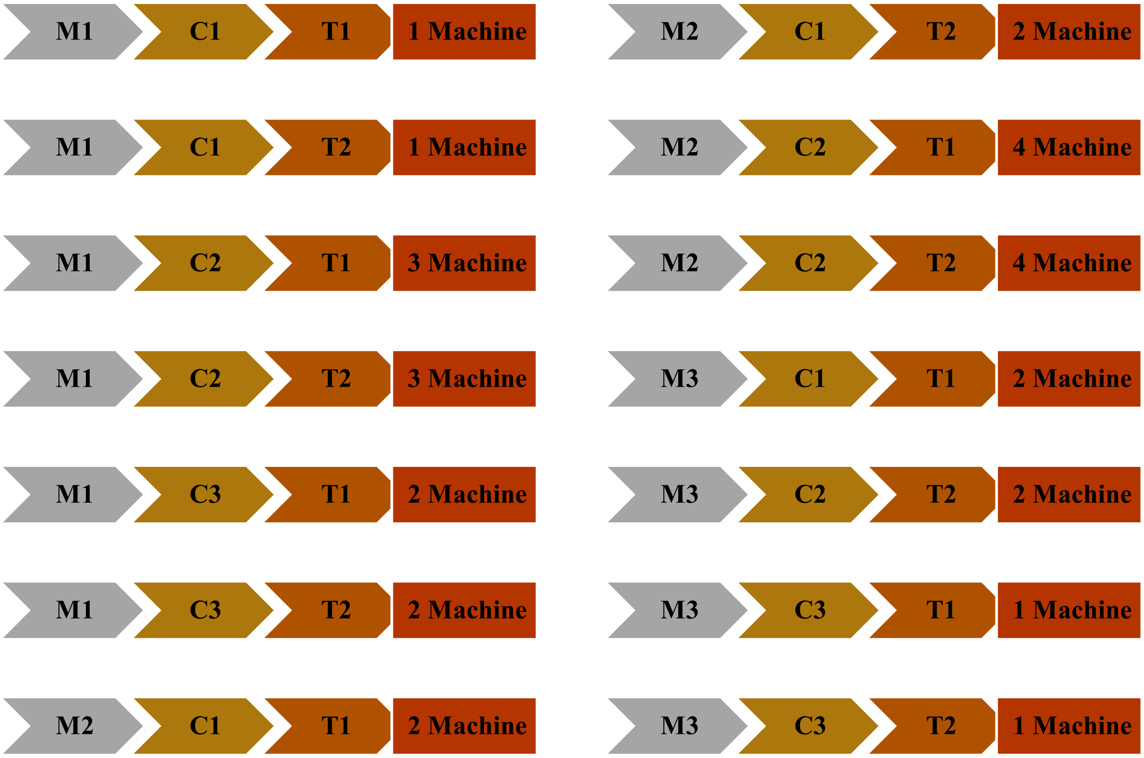

Figure 3-2 *Allocation and quantity of machine types*

Table 3-10 Number of Returned Product J to Be Acquired in Time Period T

Returned Product (J)	Time Period (T)	Value
1	1	0
1	2	0
2	1	416
2	2	375
3	1	0
3	2	0

3.3.3 Sensitivity analysis

To demonstrate the additional usability of the model at the system design and operational levels, a sensitivity analysis has been conducted to show the effects of quality levels of the returned products on the total costs as well as the total number of acquired returned products. The effects of outsourcing option of the part demands on the objective function value and the total number of acquired returned products have also been investigated. Figure 3-3 demonstrates the fluctuations of the total costs by changing the recovery rates from 0.1 to 1.0 through gradual increments of 0.1. The main assumption in the sensitivity analyses is to consider the same recovery rates for all types of the returned products. According to Figure 3-3, for the recovery rates of 0.1 to 0.5, fluctuations in the total costs are moderately higher in comparison with the recovery rates of 0.6 to 1.0. This is because of the substantial reduction of the total number of returned products to be acquired with the recovery rates of 0.6 to 1.0. Accordingly, acquiring high-quality returned products will be resulted in the reduction of objective function value. For example, for the quality level of 0.2, 1187 returned products are needed while for the quality level of 0.8, 297 returned products are acquired. Accordingly, total number of returned products are approximately 70% reduced, so objective function value will be reduced. Figure 3-4 shows the effects of variation of the recovery rates on the number of acquired returned products. There is a significant reduction in the number of returned products to be acquired especially when the recovery rates fluctuate between 0.1 and 0.5. Figure 3-4 demonstrates that by acquiring high-quality returned products, number of returned products to be bought will be reduced. Accordingly, total costs related to quality level of 0.1 is approximately 16,000,000. By considering quality level of the returned products to be 0.9, total costs are reduced to 389,310. Accordingly, 97% of the total costs can be reduced.

In order to reduce the objective function value, operational managers can consider outsourcing option of the part demands. Figure 3-5 demonstrates the effects outsourcing option on the number of acquired returned products. According to Figure 3-5, number of acquired returned products decreased from 791 to 419 while taking outsourcing option into account in satisfying the part demands. Figure 3-6 also demonstrates the effect of outsourcing option on the total costs in the objective function. According to Figure 3-6, objective function value has decreased from 5,267,561 to 2,963,616 which shows 43% improve in reducing the total costs. Our sensitivity analyses demonstrated that acquiring high-quality returned products and outsourcing option of the part demands can have firm managerial implications, in operational level, to reduce the total costs substantially.

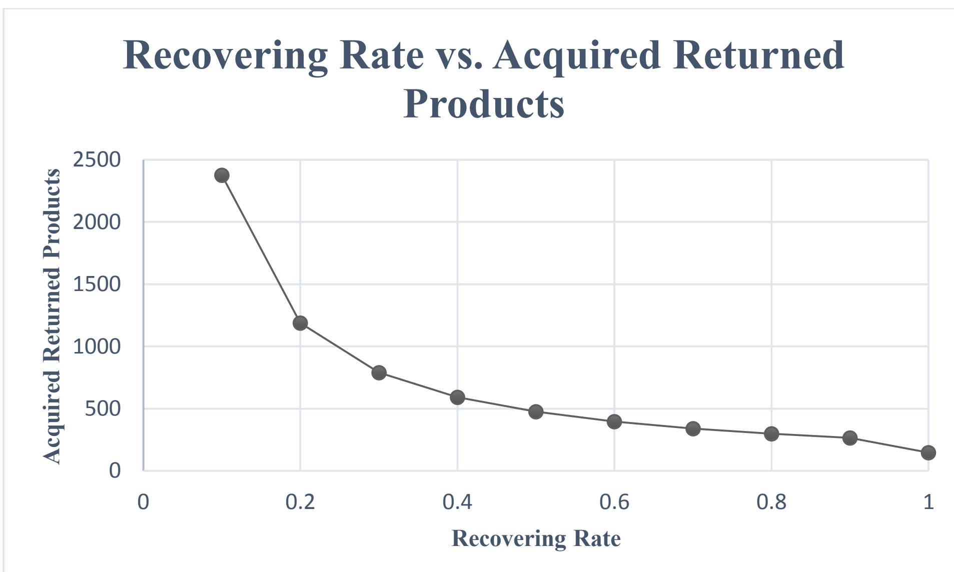

Figure 3-3 *Acquired returned products versus recovery rates*

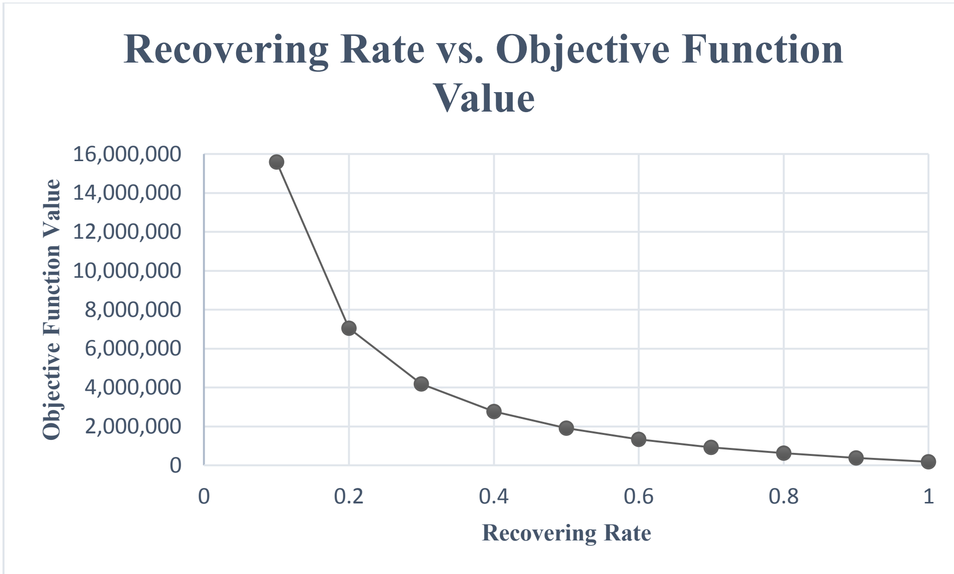

Figure 3-4 *Acquired returned products versus recovery rates*

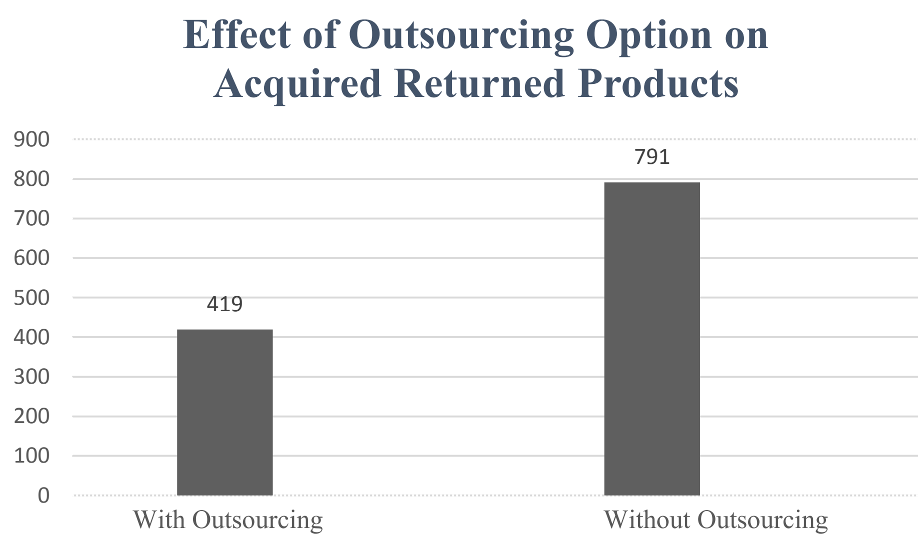

Figure 3-5 *Effect of outsourcing option versus acquired returned products*

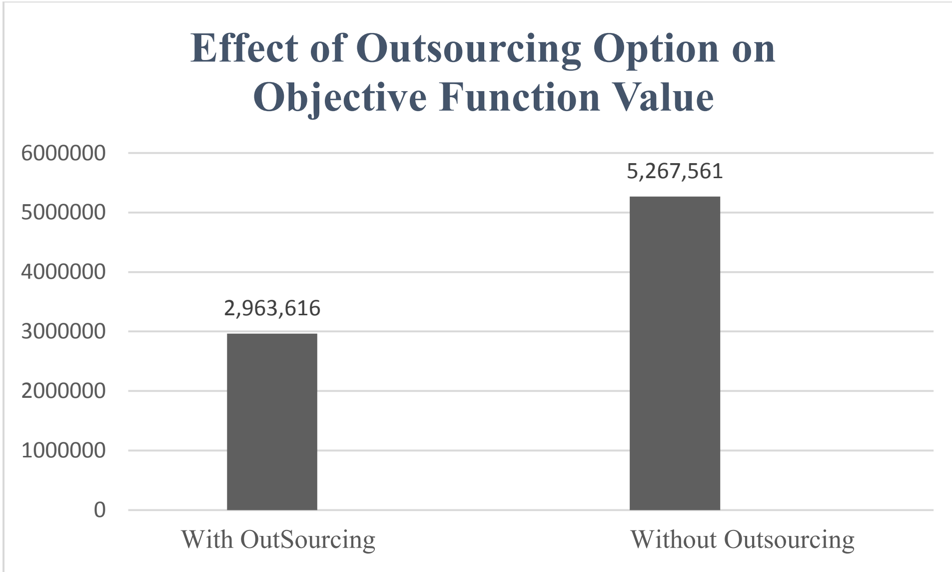

Figure 3-6 *Effect of outsourcing option versus objective function value*

3.4 Summary of the chapter

In this Chapter, a mixed integer linear programming (MILP) model, which considers the integration of production planning problem in cellular manufacturing systems bridged with the tactical planning of a closed-loop supply chain, has been developed. This is, accordingly, one preliminary step towards integration of manufacturing systems in the closed-loop supply chains to build a sustainable manufacturing enterprise. The proposed models consider several manufacturing attributes such as: multi period production settings, machine capacities, machine procurements, acquisition of the returned products, disassembly of the returned products, remanufacturing of parts having decent qualities, and disposal of parts not having enough quality to be selected for remanufacturing. Enterprises operating cellular manufacturing systems as a part of closed-loop supply chains and with sustainability objectives could use the integrated model that we propose at the design optimization and production planning stages of their activities. More precisely, the more likely users of our model are the designers of sustainable manufacturing/supply chain systems at the design stage as well as the managers running such systems at the operational level. The overall objective function of the model is to minimize 4 categories of costs including (1) machine costs: maintenance and overhead cost, relocation costs of machines, machine procurements, and machine operating cost, (2) inter-cell material handling cost, (3) remanufacturing cost of the returned products, and (4) costs associated with returned products such as acquisition, disassembly, inventory holding, and disposal costs of the returned products. The future work in this research, should involve considering several recovery options such as recycling, refurbishing, buck recycling, repair, and reuse 'as is' to design a holistic sustainable manufacturing enterprise . Investigating the large-scale instances of the proposed model and deriving effective solution methodologies for them is another direction for the future extension of this research.

Chapter 4 A mathematical model for the sustainable design of a cellular manufacturing system in the tactical planning of a closed-loop supply chain featuring alternative routings and outsourcing option

4.1 Introduction

In this chapter, design optimization of a cellular manufacturing system as a part of a sustainable closed-loop supply chain is investigated to form a sustainable manufacturing enterprise. Hence, a mathematical model is developed to coordinate the production planning of a cellular manufacturing system with the tactical planning of a closed-loop supply chain. Tactical decisions in a closed-loop supply chain encompasses making decisions on acquisition, grading, disposition, and production planning of the returned products. A closed-loop supply chain encompasses both forward and reverse flows of materials from original equipment manufacturer to the customers and vice versa. According to Figure 4- 1, returned products are remanufactured to fulfil the demands of customers. Accordingly, in the reverse chain, returned products are collected from the customer zones to be inspected and tested in the disassembly centers. Hence, returned products are pulled apart to separate all the remanufacturable components. High-quality components are shipped to remanufacturing centers in which the process of restoring returned products to "like-new" condition is performed. Low-quality components are going to be disposed.

Recognizing the suitable manufacturing layouts can highly increase the efficiency of remanufacturing processes which leads to the design of a sustainable manufacturing system. To achieve sustainability in manufacturing systems, using cellular manufacturing layouts are highly recommended [105]. The proposed model considers several manufacturing attributes such as multi-period production settings, operation sequences, alternative process routings, lot splitting, outsourcing, and reconfigurable layouts of the system, machine duplication, machine acquisition, machine adjacency requirements, and machine capacity. There are several parameters pertaining to the reverse supply chain activities including acquisition of the returned products, disassembly of the returned products, remanufacturing of parts having high qualities, and disposal of the returned products that cannot be economically recovered. Figure 4- 1 represents the material flow of the proposed sustainable cellular remanufacturing system. The overall objective function of the model is to minimize four sets of costs such as (1) machine costs: maintenance and overhead cost, relocation costs of the machines, machine procurement costs, and machine operating costs, (2) inter-cell material handling costs, (3) remanufacturing cost of the returned products, and (4) costs associated with returned products such as acquisition, disassembly, inventory holding, and disposal of the returned products. A mixed integer-linear programming (MILP) model for solving the above-described problem is formulated. The rest of the section presents the model assumptions, parameters, decision variables, formulation, as well as a detailed description of the proposed mathematical model and its linearization procedure. The cellular manufacturing system in this article has only remanufacturing option through different recovery options such as remanufacturing, refurbishing, repairing, and recycling. Total demands of the parts will be satisfied by remanufacturing returned products as well as subcontracting of the part demands.

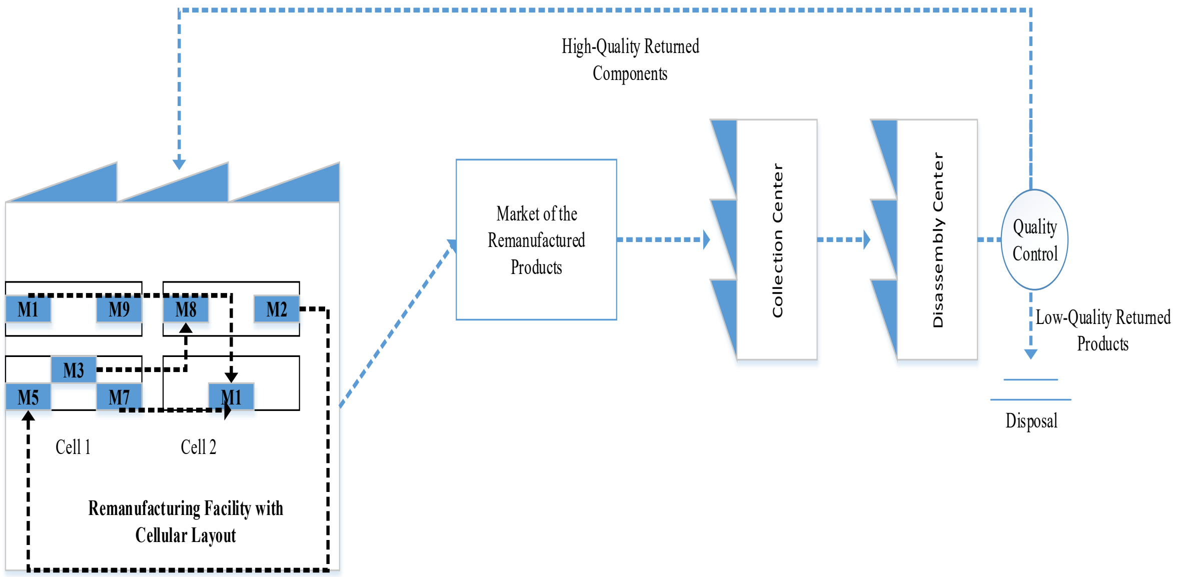

Figure 4-1 *Material flow for the proposed cellular manufacturing system in a closed-loop supply chain*

4.2 Model Assumptions

When formulating the proposed mathematical model, several specific assumptions have been taken into account as follows:

- The number of cells is constant over the planning horizon and predefined;
- The demand for each part type is deterministic and known in advance in each time period;
- The demand for each part type in each time period can be fulfilled by internal production, outsourcing, as well as inventories that can be carried over from the previous time period;
- Each machine type has a limited capacity expressed in hours during each time period;
- Reconfiguration involves the addition and removal of machines to cells and relocation from one cell to another at the beginning of each time period;

- The machine maintenance and overhead costs are known and constant over the planning horizon;
- Facility planning issues such as machines adjacency requirements and part-machine incidence matrix are considered;
- Lot-splitting and dynamic reconfiguration of the cells are considered.

4.2.1 Model parameters and decision variables

The notations used in the model are presented below followed by the objective function and set of constraints.

Problem Sets:

I: Set of part types

M: Set of machines

C: Set of cells

T: Set of time periods

J: Set of returned products

Ξ (I): Set of operation indices of part types

Ω: A set of machine pairs that should be placed in the same cell

S: A set of machine pairs that should not be placed in the same cell

Parameters

$D_{\zeta it}$	Demand of product i processed by operation ζ in time period t
Γ_i^{inter}	Intercellular movement cost of part i
$\rho_{\zeta im}$	Processing time of operation ζ of part i on machine m
π_{mt}	Time capacity of machine m in time period t
β_c	Lower size limit of the cells
α_c	Upper size limit of the cells
R_m	Installation cost of the machine m
K_m	Removal cost of the machine m
M^{∞}	A large positive and integer number

ε_{it}	Holding/Carrying cost of part type i in time period t
A_m	Machine availability in time period one before procuring any machines
η_m	Machine maintenance and overhead costs
σ_m	Machine procurement cost
γ_m	Operating cost of machine type m
E_i	Production cost per part type i
Φ_{jt}	Unit cost to acquire returned product j in time period t
κ_{jt}	Setup cost for disassembling returned product j in time period t
τ_{jt}	Unit cost to disassemble returned product j in time period t

θ_{jt}	Unit inventory cost for returned product j in time period t
U_i	Average recovering rate of part i from all returned products
B_{ij}	Number of parts i contained in product j
χ_j	Disposal cost of returned product j
$\nabla_{\zeta im}$	If operation ζ of part i can be done on machine type m
θ_{it}	Cost of subcontracting part i in time period t

Decision Variables

N_{mct}	Number of type m machines presented in cell c at the beginning of time period t

ς_{mct}	=1, if machine type m is to be assigned to cell c during time period t; = 0 otherwise
Y^{+}_{mct}	Number of type m machines added in cell c at the beginning of time period t
Y^{-}_{mct}	Number of type m machines removed from cell c at the beginning of time period t
ν_{mt}	Number of machines of type m procured at time t
$\hat{A}_{mt}$	Quantity of machines type m available at time period t after accounting for machines that have been procured
$Q_{\zeta it}$	Number of part inventory of type i processed by ζ operation kept in time period t and carried over to period (t + 1)
$X_{\zeta imct}$	Number of parts of type i processed by operation ζ on machine m in cell c in time period t

$O_{\zeta it}$ Number of outsourced parts for each operation ζ of a part type i

$Z_{\zeta imct}$ = 1, if operation ζ of part type i is carried out on machine type m in cell c in period t; = 0 otherwise

d_{jt} Number of returned product j to be disassembled in time period t

r_{jt} Number of returned product j to be acquired in time period t

Objective Function

<u>Minimize</u>

$$\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{m=1}^{M} N_{mct} * OV_m$$

$$+\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{m=1}^{M} R_m * Y_{mct}^{+}$$

$$+\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{m=1}^{M} K_m * Y_{mct}^{-}$$

$$+\sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{\zeta=1}^{\Xi} \epsilon_{it} * Q_{\zeta it}$$

$$+\sum_{t=1}^{T}\sum_{i=1}^{I} \beta_{it} * O_{\zeta it}$$

$$+ \sum_{t=1}^{T} \sum_{c=1}^{C} \sum_{i=1}^{I} \sum_{\zeta=1}^{\Xi-1} \Gamma_i^{inter} |X_{\zeta+1imct} - X_{\zeta imct}|$$

$$+ \sum_{t=1}^{T} \sum_{c=1}^{C} \sum_{m=1}^{M} \sum_{i=1}^{I} \sum_{\zeta=1}^{\Xi} X_{\zeta imct} * E_i$$

$$+ \sum_{t=1}^{T} \sum_{m=1}^{M} v_{mt} * \sigma_m$$

$$+ \sum_{t=1}^{T} \sum_{c=1}^{C} \sum_{m=1}^{M} \sum_{i=1}^{I} \sum_{\zeta=1}^{\Xi-1} X_{\zeta imct} * t_{\zeta im} * \gamma_m$$

$$+ \sum_{t=1}^{T} \sum_{j=1}^{J} \Phi_{jt} * r_{jt}$$

$$+ \sum_{t=1}^{T} \sum_{j=1}^{J} \kappa_{jt} * \delta_{jt}$$

$$+ \sum_{t=1}^{T} \sum_{j=1}^{J} \tau_{jt} * d_{jt}$$

$$+ \sum_{t=1}^{T} \sum_{j=1}^{J} \theta_{jt} * f_{jt}$$

$$+ \sum_{t=1}^{T} \sum_{i=1}^{I} \sum_{j=1}^{J} (1 - U_i) * \chi_j * B_{ij} * d_{jt}$$

<u>Subject to:</u>

$$Q_{\zeta it-1} + \sum_{m=1}^{M} \sum_{c=1}^{C} X_{\zeta imct} - Q_{\zeta it} + O_{\zeta it} = D_{\zeta it}; \forall (\zeta, i, t) \qquad 1.1$$

$$N_{mct} = N_{mct-1} + Y_{mct}^{+} - Y_{mct}^{-}; \forall (m, c, t) \qquad 1.2$$

$$\beta_c \leq \sum_{m=1}^{M} N_{mct} \leq \alpha_c; \forall (c, t) \qquad 1.3$$

$$\sum_{i=1}^{I} \sum_{\zeta=1}^{\Xi} X_{\zeta imct} \cdot \rho_{\zeta im} \leq N_{mct} \cdot \pi_{mt}; \forall (m, c, t) \qquad 1.4$$

$X_{\zeta imct} \leq M . Z_{\zeta imct}; \forall (\zeta, i, m, c, t)$ 1.5

$\widehat{A}_{m(t=1)} = A_{m(t=1)} + v_{m(t=1)}; \forall (m)$ 1.6

$\widehat{A}_{m(t+1)} = \widehat{A}_{mt} + v_{m(t+1)}; \forall (m)$ 1.7

$\sum_{c=1}^{C} N_{mct} \leq \widehat{A}_{mt}; \forall (m, t)$ 1.8

$f_{jt} + d_{jt} - f_{jt-1} = r_{jt}; \forall (j, t)$ 1.9

$d_{jt} \leq M. \delta_{jt}; \forall (j, t)$ 1.10

$\sum_{m=1}^{M} \sum_{c=1}^{C} X_{\zeta imct} \leq U_i \sum_{j=1}^{J} B_{ij}. d_{jt}; \forall (i, t)$ 1.11

$Z_{\zeta imct} \leq \nabla_{\zeta\, im}; \forall (\zeta, i, m, c, t)$ 1.12

$N_{mct} \leq M. \varsigma_{mct}; \forall (m, c, t)$ 1.13

$\varsigma_{mct} \leq N_{mct}; \forall (m, c, t)$ 1.14

$\varsigma_{m_{ct}^{a}} + \varsigma_{m_{ct}^{b}} \leq 1; \forall (c, t) \qquad (m^a, m^b) \in \Omega$ 1.15

$\varsigma_{m_{ct}^{c}} - \varsigma_{m_{ct}^{d}} = 0; \forall (c, t) \qquad (m^c, m^d) \in S$ 1.16

$N_{mct}, Y_{mct}^{+}, Y_{mct}^{-} \geq 0$ and integer; $\forall (m, c, t)$ 1.17

$\omega_{it}, O_{\zeta it}, Q_{\zeta it}, X_{\zeta imct} \geq 0$ and integer; $\forall (\zeta, i, m, c, t)$ 1.18

$v_{mt}, \widehat{A}_{mt}, \geq 0$ and integer; $\forall (m, t)$ 1.19

$\varsigma_{mct}, Z_{\zeta imct} \in \{0, 1\}; \forall (\zeta, i, m, c, t)$ 1.20

Model objective Function: The objective function of the model consists of several cost terms. The first term shows the maintenance and overhead costs of the machines. The second term demonstrates the cost of machine installations while the third term represents the cost of machine removals. The fourth term is pertinent to the inventory carrying cost of the parts. The fifth term shows the cost of outsourcing of each operation of part types in each time period. The sixth term addresses the cost of intercellular movements of the parts between the cells. The seventh term is relevant to the production costs of the remanufactured components. The eighth term represents machine procurements cost. The ninth term demonstrates machine operating cost. The tenth term represents acquiring costs of the returned products. The eleventh term represents the setup cost for disassembling operations. The twelfth term addresses the disassembling costs of the returned products. The thirteenth term shows the inventory holding cost for the returned products, and the last term, term number fourteen, addresses the disposal cost of the returned products.

Model Constraints: The objective function of the model is subjected to constraints as follows: Constraint (1.1) demonstrates that the demands for each operation of part type i in each time period can be fulfilled by producing remanufactured products, outsourcing option of the part demands, and the inventory carried over from previous time period subtracting the inventory of the current time period. Constraint (1.2) demonstrates the number of machines of type m at the beginning of each time period is equal to number of machines in the previous time period considering installations and removals of machines of type m in cell c at the beginning of each time period t. The size of the cells is user-defined through constraint (1.3) where the number of machine assignments of each type should be lied between the lower size and upper size of the cells.

Constraint (1.4) ensures that the capacity of machines would not be exceeded. Constraint (1.5) indicates that the number of parts produced can be positive only if $Z_{\zeta imct}$ = 1, that is, it has been decided that part i would be produced by operation ζ on machine m in cell c in time period t. Constraint (1.6) is relevant to the availability of machines for time period 1 taking into consideration machine procurements option. The total number of machines of each type available in the system is equal to the machine availability before machine procurements in addition to the number of machines acquired in the first time-period. Constraint (1.7) indicates that machine availabilities for the subsequent time periods excluding time period 1 can be recorded. The number of machines procurements in the current time period along with the number of machines that have been acquired in all the preceding time periods demonstrates total available machines in the system. Constraint (1.8) states that total number of machines in each cell should not exceed the total number of available machines. Constraint (1.9) shows that the total number of returned products to be acquired can be calculated through the summation of total number of returned products to be kept in inventory for the current time period as well as total number of returned products to be disassembled for the current time period subtracting the amounts of inventory carried over from the previous time period. Constraint (1.10) indicates a logical constraint for disassembling activities. Constraint (1.11) takes to account the bill of materials (BOM) and the quality levels of the returned products. It represents that the quantity of parts acquired from returned products is dependent to their quality levels. Constraint (1.12) ensures that each operation of a part is assigned to appropriate machines according to part-machine incidence matrix. Constraint (1.13) and Constraint (1.14) are for setting ς_{mct} to 1 if at least one machine of type m is located in cell c during time period t. Constraint (1.15) is to ensure that machine pairs included in Ω should not be placed in the same cell. Constraint (1.16) is also to ensure that machine pairs in S should be placed in the same cell. Constraint (1.17), constraint (1.18), constraint (1.19), and constraint (1.20) specify the logical binary and non-negativity integer requirements on the decision variables.

4.2.2 Linearizing the Objective Function

The objective function of the model is a non-linear function due to the use of absolute value in the fifth cost element in the objective function. This term can be linearized using the procedure given by Ahkioon et al. [16] as follows:

The absolute value $\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{i=1}^{I}\sum_{\zeta=1}^{\Xi-1}\xi_i^{inter}\left|X_{\zeta+1imct} - X_{\zeta imct}\right|$ can be linearized by introducing non-negative integer variables η_{zzimct} and $\digamma_{zzimct}$. The term then can be replaced by the following added constraint:

$$X_{\zeta+1imct} - X_{\zeta imct} = \eta_{\zeta imct} - \digamma_{\zeta imct};\ \forall\ (\zeta, \mathrm{i}, \mathrm{c}, \mathrm{t}) \qquad 1.22$$

$\eta_{\zeta imct} + \digamma_{\zeta imct}$ is substituted for the absolute value in the objective function. After this term is linearized, the objective function of the mixed-integer programming model has linear terms only. All constraints in the mathematical model are linear as well. The number of variables and number of constraints in the model are presented in Table 1 and 2 respectively.

Table 4-1 Number of variables in the linearized model

Name of variables	Nature of variable	Variable count	Name of variables	Nature of variable	Variable count
N_{mct}	General Integer	M×C×T	$O_{\zeta it}$	General Integer	Ξ×I×T
Y_{mct}^{+}	General Integer	M×C×T	$Z_{\zeta imct}$	Binary	Ξ×I×M×C×T
Y_{mct}^{-}	General Integer	M×C×T	r_{jt}	General Integer	J×T
ς_{mct}	Binary	M×C×T	d_{jt}	General Integer	J×T
v_{mt}	General Integer	M×T	δ_{jt}	General Integer	J×T
$\hat{A}_{mt}$	General Integer	M×T	f_{jt}	General Integer	J×T
$Q_{\zeta it}$	General Integer	Ξ×I×T	$X_{\zeta imct}$	General Integer	Ξ×I×M×C×T
$\eta_{\zeta imct}$	General Integer	Ξ×I×M×C×T	$\text{ſ}_{\zeta imct}$	General Integer	Ξ×I×M×C×T
Total: 4×(M×C×T) + 4×(Ξ×I×M×C×T) + 4×(J×T) + 2×(M×T) + 2×(Ξ×I×T)					

Table 4-2 Number of constraints in the linearized model

Equation number	Total count	Equation number	Total count
1.1	Ξ×I×T	1.10	J×T
1.2	M×C×T	1.11	I×T
1.3	C×T	1.12	Ξ×I×M×C×T
1.4	M×C×T	1.13	M×C×T
1.5	Ξ×I×M×C×T	1.14	M×C×T
1.6	1×M	1.15	C×T
1.7	1×M	1.16	C×T
1.8	M×T	1.21	Ξ×I×M×C×T
1.9	J×T		
Total: 1×(I×T) + 4×(M×C×T) + 3×(C×T) + 2×(1×M) + 1×(M×T) + 2×(J×T) + 3×(Ξ×I×M×C×T) + 1×(Ξ×I×T)			

4.3 Numerical example

One example problem is solved with the use of IBM ILOG CPLEX Optimization Studio 12.7/OPL, a commercially available optimization software, performed on Intel® Core™2.67 GHz workstation. This example problem which can be considered a large-sized instance of the model based on its number of decision variables and constraints is explained thoroughly to illustrate the design issues in cellular manufacturing systems. The data sets used are based on the data used by Ahkioon et al. [30] as well as Chen and Abrishami [19]. Unknown parameters were extracted by cross-referencing between the data sets containing them to be incorporated inside the other data sets missing that information.

4.3.1 Example Problem

In solving the Example Problem, 10 machine types, 25-part types, 2 planning periods, 3 cells, and 3 returned products are considered. All the part types have between 5 to 9 operations. Economic analyses are done to investigate the effects of outsourcing option of the part demands on the total costs and production parameters. There are several features in designing the proposed manufacturing enterprise considered in this article including dynamic reconfiguration of cells and alternative routings. By eliminating such features one at a time from the basic model, impacts of these features on the solution of the mathematical model are going to be investigated. Table 3 demonstrates the general features of the Example Problem.

Table 4-3 Generic attributes of the Example Problem

No. of parts	No. of machines	No. of cells	No. of retuned products	No. of operations	No. of binary variables	No. of integer variables	No. of constraints
25	10	3	3	5-9	13,566	38,638	40,252

4.3.2 Input data and problem size

The input data of the Example Problem are given in Tables 4-4 and 4-5. Table 4-4 demonstrates the value of the parameters corresponding to the mathematical model proposed. Table 4-5 from Defersha and Chen [10] contains the data related to routings of different operations of the part types which can be done on different machine types.

Table 4-4 Cellular manufacturing data sets for the second instance

Parameter	Value
Demand for part type i at time period t	30000-31000
Processing time of operation ζ of part type i on machine m	0.2
Production cost per part type i	0.5
Inventory holding cost per part type i per time period	0.2
Outsourcing cost per part type i	250-1000
Intercellular material handling cost per part type i	5
Quantity of machine type m available at time period t	2-5
Capacity of one unit of machine type m during one-time period	10000-30000
Operating cost per unit time per machine type m	10
Maintenance and overhead costs per machine type m	10
Procurement cost per machine type m	200-1000
Machine Installation cost	500
Machine Removal Cost	150
Upper limit cell size	25
Lower limit cell size	2
Acquiring cost of the returned product j in time period t	15-35
Setup cost for disassembling returned product j in time period t	20-35

Table 4-4 continued

Parameter	Value
Inventory cost for returned product j in time period t	30-50
Disassembly cost of returned product j in time period t	15-35
Average recovering rate of returned product j	0-1
Number of part i contained in product j	5-15
Disposal cost of the returned product j	200-400
Pair of machines that should be located in the same cell	{1,3}
Pair of machines that should not be located in the same cell	{2,4} and {6,9}

Table 4-5 Routes and alternative routings for the second instance

Part no.	Operation no								
	1	2	3	4	5	6	7	8	9
1	1,2	3	1	3	4				
2	8	8	8	7	7	7	9,10	9,10	9,10
3	2	2	2	1,2	1,2	6	6	6	
4	5	5	5	9,10	9,10				
5	8	9,10	9,10	7	7	7	7	8	8
6	5	5	5	1,2	1,2	9,10			
7	1,2	1,2	1	3	3,4	4	1	1	5
8	2	2	6	6	2	2			
9	7	7	8	9,10	9	8	8		
10	5	5	5	5	9	9			
11	1,2	3	3,4	1	2	6			
12	2	2	1,2	7	6				
13	7	7	7	8	8	8	5	5	5
14	6	6	6	5	5				
15	1	3	3,4	1	4	8			
16	8	8	7	7	7				
17	1,2	2	2	6					
18	3	3	3,4	1,2	4				
19	5	5	5	9,10	9,10	9,10			
20	2	2	2	1,2	1,2	2	6	6	
21	9	9	7	7	7	6	8	8	
22	1,2	1	3	3,4	2	6			
23	1,2	1,2	5	5	5	9,10			
24	6	6	2	2	2				
25	7	7	8	8	8	9			

4.3.3 Solution of Example Problem

Table 4-6 and Table 4-7 demonstrate part-machine cell allocation for time period 1 and time period 2 respectively. According to Table 4-6 and Table 4-7, parts are produced in multiple cells with the use of different machines in two consecutive time periods. Table 4-6 and Table 4-7 show also the assignments of machine types to cells at the beginning of each time period, as well as allocation of parts to cells and machines for internal production. Alternative process routings of part types can also be shown in Tables 4-6 and 4-7 given the fact that similar operations of the parts are carried out on different machines and/or machine types and/or cells. Noteworthy, table 4-6 shows the operation sequences of different part types pertinent to time period 1 and table 4-7 shows the operation sequences for the second time period. For instance, in Table 4-6 operations 7, 8 and 9 of the part type 2 are done in the cell 1 and cell 2 with the use of machine type 9 and 10 at the same time. Operations 1 to 6 of the same part type are done in cell 1 with the use of machines 8 and 7 respectively. Operations 6, 7, and 8 of part type 3 are done with the use of machine 6 in cells 2 and 3. Although operations 1 to 5 of the part type 3 are done with the use of machine 2 in cell 3. Operations 1 to 5 of the part type 10 are done with the use of machine 2 and 5 in the cell 2 and 3 respectively, and operations 5 and 6 of the same part type are done with the use of machine 9 in cell 1. However, all the operations of part type 16 can be done in cell 1 with the use of machine type 7 and 8.

In Table 4-7, for example, operations 1, 2, 3, 7, 8, and 9 of part type 13 are done using machine types 5 and 8 in cell 2 and operations 4, 5, and 6 of the same part are done resorting to machine 8 in cell 1. All the operations related to part type 17 are done with the use of machine 2 and 6 in cell 2. Operation 1 to 13 of part type 18 are done with the use of machine 3 in cells 1 and 3 concurrently.

Operation 4 of the part 18 is implemented on machine 2 in cell 2, and its last operation is done with the use of machine 4 in cell 1. Operation 1 and 2 of part type 21 is completed utilizing machine 9 in cell 1. However, operations 3, 4, 5, 7, and 8 are done with the use machines 7 and 8 in cell 1. Operation 6 of the part type 21 is implemented on machine 6 in cell 3. Finally, operations 1 and 2 of part type 24 is carried out on machine 6 in cell 3, and operations 3, 4, and 5 of the same part type is done on machine 2 in cell 2.

Table 4-6 Part-cell assignment for period 1

Cell	Machines/Part Types		1	2	3	10	16
C1	M1	2					
	M3	2	ζ2				
	M4	2	ζ4 ζ5				
	M5	3					
	M7	2		ζ4 ζ5 ζ6			
	M8	3		ζ1 ζ2 ζ3			
	M9	3		ζ7 ζ8 ζ9		ζ5 ζ6	
	M10	2					
C2	M1	1	ζ1 ζ3				
	M2	7				ζ1 ζ2 ζ3ζ4	
	M3	1					
	M5	3					
	M6	1			ζ6 ζ7 ζ8		
	M7	3					ζ3 ζ4 ζ5
	M8	2					ζ1 ζ2
	M10	2		ζ7 ζ8 ζ9			

Table 4- 6 continued

Cell	Machines/Part Types	1	2	3	10	16
C3	M1 1					
	M2 4			$\zeta 1$ $\zeta 2$ $\zeta 3$ $\zeta 4 \zeta 5$		
	M3 1					
	M5 1				$\zeta 1$ $\zeta 2$ $\zeta 3$ $\zeta 4$	
	M6 4			$\zeta 6$ $\zeta 7$ $\zeta 8$		
	M8 1					

Table 4-7 Part-cell assignment for period 2

Cell	Machines/ Part Types	13	17	18	21	24
C1	M1 1					
	M3 3			ζ1 ζ2 ζ3		
	M4 2			ζ5		
	M5 2					
	M7 3				ζ3 ζ4 ζ5	
	M8 3	ζ4 ζ5 ζ6			ζ7 ζ8	
	M9 3					
	M10 1					
C2	M1 1					
	M2 6			ζ4		ζ3 ζ4 ζ5
	M3 2					
	M5 3	ζ7 ζ8 ζ9				
	M7 4					
	M8 3	ζ1 ζ2 ζ3				
	M9 1				ζ1 ζ2	

Table 4- 7 continued

Cell	Machines/ Part Types		13	17	18	21	24
C3	M1	1					
	M2	2		$\zeta 1$ $\zeta 2$ $\zeta 3$			
	M3	2			$\zeta 1$ $\zeta 2$ $\zeta 3$		
	M6	4		$\zeta 4$		$\zeta 6$	$\zeta 1$ $\zeta 2$
	M8	1					

Table 4-8 demonstrates exactly how the demands of each operation of a part type can be fulfilled with the use of internal production, outsourcing, and additional inventory from previous time periods that can be carried over to the current time period. According to Table 4-8, internal production and outsourcing option have been selected for satisfying the demands of the first operation of part type 10 that is 2078 of part type 10 in the first time period and 1845 of the same part type in the second time period are going to be subcontracted. However, internal production and inventory holding options are applied for satisfying the demands of the first operation of the part type 2 that is 10203 parts of type 2, surplus on total demand in the first time period, are carried over to the second time period to fulfill the total demand. Noteworthy, CPLEX is able to solve the mathematical model to optimality in 78.73 seconds.

Table 4-8 Comparison of production plans for operation 1 of part types 2 and 10

Part Type 2	With Outsourcing	Time Period 1	Time Period 2
	Internal production	40653	20797
	Outsourcing	0	0
	Inventory held	10203	0
	Demand	30450	31000
Part Type 10	With Outsourcing	Time Period 1	Time Period 2
	Internal production	28662	28607
	Outsourcing	2078	1845
	Inventory held	0	0
	Demand	30740	30452

4.3.4 Solution analyses for the Example Problem

Outsourcing option of the part demands: To increase the flexibility in satisfying the part demands, outsourcing option has been considered in the mathematical model proposed in this article. In order to investigate the impacts of outsourcing option on the objective function value and number of returned products need to be acquired in different time periods, we recalculate the Example Problem without this option. Table 9 demonstrates that with the use of outsourcing option of the part demands 6,881,469 can be saved in the total costs. Table 4-9 also shows that the number of acquired returned products has been increased from 9545 to 10200 without the consideration of outsourcing option. In the proposed mathematical model in which a dynamic cellular manufacturing system has been integrated with the tactical planning of a closed-loop supply chain, outsourcing option of the part demands has economic efficiency. By considering internal production solitary, one needs to incur the costs of acquiring returned products, setup for disassembling the returned products, disassembly of the returned products, and inventory holding of the returned products as well. Also, machine costs such as overhead and maintenance costs, machine acquisition cost, machine procurement cost, and machine operational cost have to be incurred for internal production. Production costs per unit also need to be considered in internal production. Hence, cost savings are achieved by considering outsourcing option of the part demands.

Table 4-9 Impacts of outsourcing option on the total costs and number of returned products

Example Problem 2	Objective function value	Acquired returned products
With Outsourcing	387,061,959	9,545
Without Outsourcing	393,943,428	10,200

Cost Savings: Cost savings may be the outcomes of applying reconfiguration and routing flexibility in designing cellular manufacturing systems. To investigate the cost saving as a result of these manufacturing attributes, Example Problem is solved by eliminating these attributes one at a time. Initially, the original model is enforced to lose its reconfigurability with the use of the constraint:

$Y^{+}_{mct} = Y^{-}_{mct} = 0, \qquad t \geq 2$

Alternative process routings of the part types can be banned by changing the part-machine incidence matrix. Mathematical model can be forced to select only one machine at a time by assigning 0 to each operation of a part that can be done on different machines on the part-machine incidence matrix. The results are summarized in Table 4-10.

Table 4-10 Cost savings by adding several manufacturing attributes

With outsourcing	Objective Function Value	Cost Saving
Dynamic reconfiguration	387,285,362	223,403
Alternative routings	392,041,019	4,979,060

According to table 4-10, eliminating dynamic reconfiguration will be resulted in the cost escalation of the objective function value. Accordingly, objective function value will be increased from 387,061,959 to 387,285,362 showing 223,403 monetary unit to be saved. By considering alternative process routing in Table 4-10, 4,979,060 monetary unit can be saved.

4.4 Computational Experiments

To further illustrate the proposed model, the mathematical model is solved for six other scenarios. According to Table 4-11, all the scenarios are solved with the use of use of IBM ILOG CPLEX Optimization Studio 12.7/OPL. For all the scenario problems, number of returned products, number of time periods, and number of operations, number of machine types, number of parts, and number of cells are reported. Number of decision variables and number of constraints for each scenario is also reported. All the scenario problems have been solved to optimality. According to

Table 4-11, solution gaps for the last two scenarios are negligible and can be ignored. Table 4-11 demonstrates that CPLEX software is able to solve the mathematical model for different instances in a small amount of computational time. The smallest instance takes only 0.66 seconds to be solved. Accordingly, as the problem instances get larger in terms of their number of decision variables and number of constraints, the solution times varies in somewhat a small gap. Hence, the second and third scenarios can be solved in 3.74 and 1.75 seconds respectively. The fourth scenario, which can be realized as a real-sized instance regarding the literature review, can be solved in 24.84 seconds. The last two scenarios, namely scenarios 5 and 6, can be considered as large-sized instances of the model which can be solved in 175.22 and 189.78 seconds respectively.

A series of economic analyses are conducted in Table 4-12 for all the scenarios to investigate the effects of the elimination of outsourcing, alternative process routings, and dynamic reconfiguration from the mathematical model. According to Table 4-12, elimination of outsourcing, alternative process routings, and dynamic reconfiguration will result in augmentation of total cost for all the scenarios. Table 4-12 shows that the effects of eliminating outsourcing and alternative process routings on increasing the total cost are more important than dynamic reconfiguration with respect to the percentage of cost savings. According to Table 4-12, the maximum cost savings by adding outsourcing to the model is pertinent to scenario 4 in which the objective function is improved by 2.04 %. Hence, by eliminating outsourcing, total cost is increased from 140,995,521 to 144,934,228 monetary unit in scenario 4. Adding outsourcing to the model improves the objective functions of the other instances of the model ranging from 0.19 % for the scenario 1 to 2.04 % for the scenario 4. According to Table 4-12, maximum cost savings by adding alternative process routings to the model is related to the scenario 5 and scenario 6 in which the objective function is improved by 10.60 % and 10.59 % respectively. Therefore, by the elimination of alternative process routings in scenario 5, total cost is increased from 387,058,487 to 432,955,106 monetary unit. Similarly, objective function of the scenario 6 is increased from 387,068,294 to 432,945,323 by the elimination of alternative process routings. Adding alternative process routings to the model improves the objective functions of the other instances of the model ranging from 1.19 % for the scenario 2 to 10.60 % for the scenario 5. Adding dynamic reconfiguration also improves the objective function of the problem instances ranging from 0.0018 % for the scenario 3 to 0.128 % for the scenario 6. For example, elimination of dynamic reconfiguration in scenario 6 will result in escalation of the total cost from 387,068,294 to 387,564,764.

Table 4-11 Different problem scenarios

Problem Scenario	Number of returned products	Number of time periods	Number of Operations	Number of machine types	Number of parts	Number of cells	Number of variables	Number of Constraints	Objective Function Value	Solution Time (Seconds)	Gap (%)
1	3	2	5-9	3	3	3	2040	1608	50,513,182	0.66	0.00
2	3	4	5-9	3	3	5	6624	5146	50,537,006	3.74	0.00
3	3	2	5-9	6	5	3	6468	5028	82,868,768	1.75	0.00
4	3	2	5-9	6	10	4	16,896	13,108	140,995,521	24.84	0.00
5	3	2	5-9	10	25	6	103,404	79,452	387,058,487	175.22	0.001
6	3	4	5-9	10	25	3	104,328	80,094	387,068,294	189.78	0.001

Table 4-12 Solution analyses for different problem scenarios

Problem Scenario	Objective Function without outsourcing	Percentage of cost saving with outsourcing	Objective function without alternative process routings	Percentage of cost saving with alternative process routings	Objective Function without dynamic reconfiguration	Percentage of cost saving with dynamic reconfiguration
1	50,611,121	0.19	52,546,740	3.86	50,731,326	0.0043
2	50,638,473	0.20	51,147,319	1.19	50,539,930	0.0057
3	83,803198	1.11	86,996,578	4.74	82,870,311	0.0018
4	143,934,228	2.04	144,208,717	2.22	141,006,720	0.007
5	393,932,838	1.74	432,955,106	10.60	387,359,970	0.077
6	393,946,065	1.74	432,945,323	10.59	387,564,764	0.128

4.5 Sensitivity Analysis

To investigate the effects of changing recovery rate of the returned products on total costs and total number of returned products to be acquired, sensitivity analyses are done in this section. The assumption in sensitivity analyses is to consider the same recovery rate for all types of the returned products. Figure 4-2 demonstrates the fluctuations of the total costs by changing the recovery rates from 0.1 to 0.9 through gradual increments of 0.1 without taking outsourcing into consideration. According to Figure 4-2, for the recovery rates between 0.1 and 0.5, reductions in the total costs are moderately higher in comparison with the recovery rates between 0.6 and 0.9. Accordingly, one probable reason to interpret this trend could be the substantial reduction in the total number of returned products to be acquired with the recovery rates of 0.6 to 0.9. Figure 4-3 also shows the effects of the recovery rate of the returned products on the number of returned products to be acquired. There is a significant reduction in the number of returned products to be acquired especially when the recovery rates fluctuate between 0.1 and 0.5. Figure 4-4 demonstrates the fluctuations of the total costs by changing the recovery rates between 0.1 and 0.9 by considering gradual increments of 0.1 while taking outsourcing into account with somehow the similar behavior in Figure 4-2. Figure 4-5 demonstrates that the number of returned products to be acquired are decreased while the recovery rate changes incrementally from 0.1 to 0.9. Figure 4-6 shows that the objective function value is decreased by considering outsourcing option of the part demands for almost all the quality levels. In Figure 4-6, “green” curve shows the improvements in the objective function. Figure 4-7 also shows that the total number of returned products are decreased by considering outsourcing for almost all the quality levels. Accordingly, “blue” curve shows the reductions in the total number acquired returned products. Figure 8 is pertinent to the effects of taking alternative routings into account. Figure 4-8 shows that for all the quality levels, considering alternative routings in the mathematical model will decrease the objective function value. Accordingly, for low quality levels between 0.1 and 0.5, the effects of alternative routing on the total costs are smaller while for higher quality levels between 0.6 and 0.9, alternative routings can improve the objective function value more significantly.

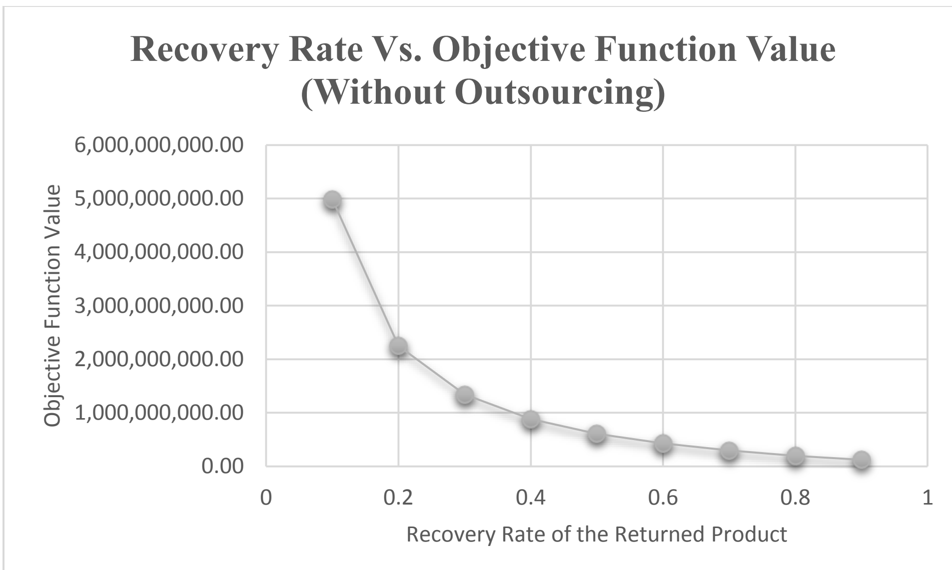

Figure 4-2 *Recovery rates versus objective function value (Without Outsourcing)*

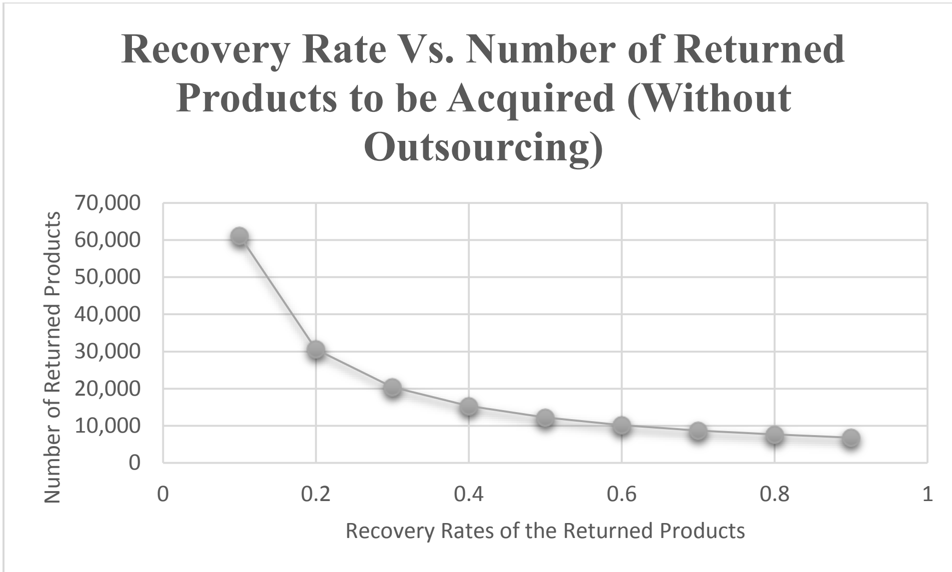

Figure 4-3 *Recovery rates versus number of returned products to be acquired (Without Outsourcing)*

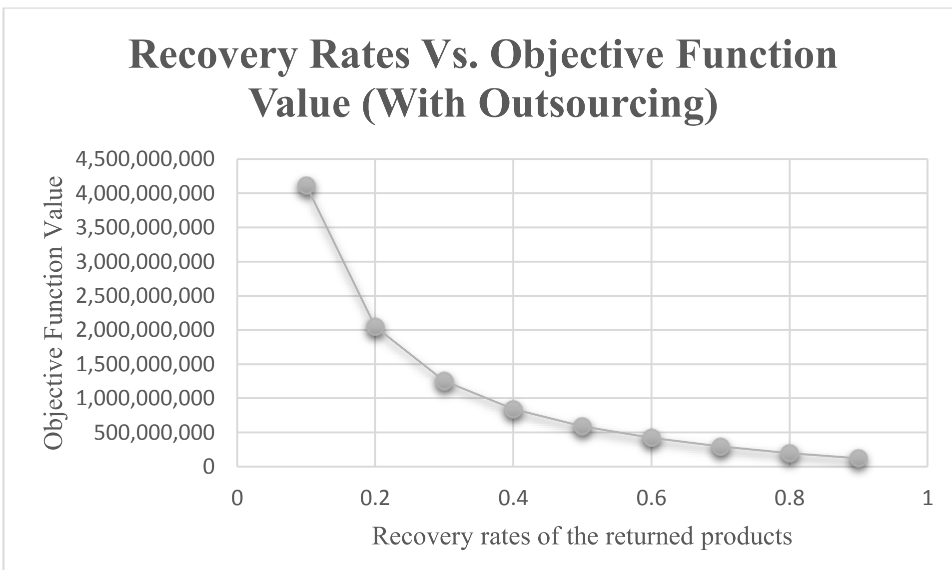

Figure 4-4 *Recovery rates versus objective function value (With Outsourcing)*

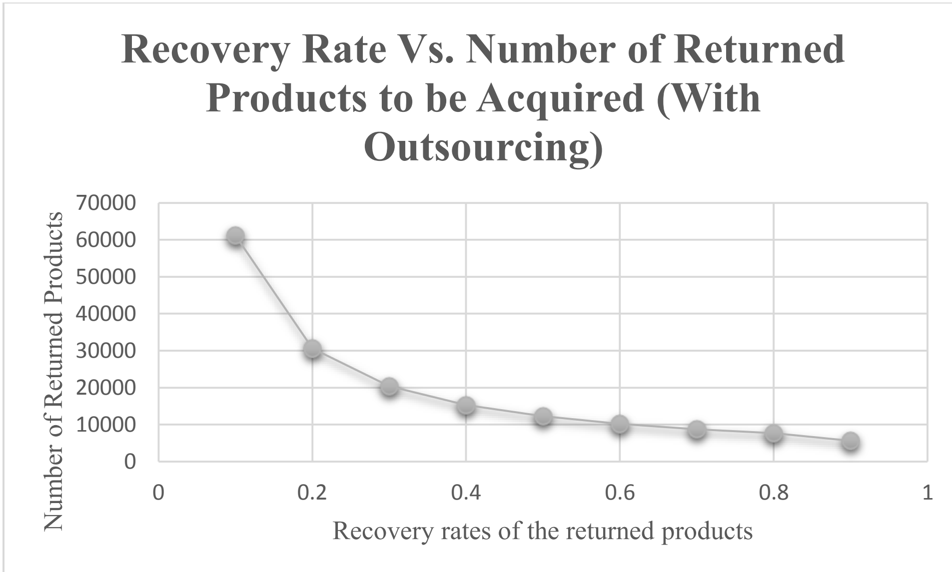

Figure 4-5 *Recovery rates versus number of returned products to be acquired (With Outsourcing)*

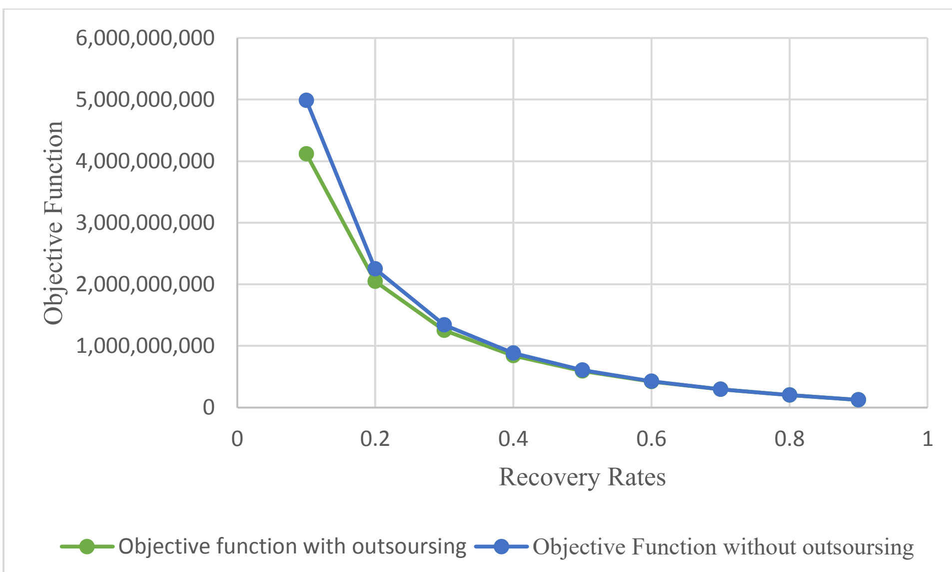

Figure 4-6 *Effect of Outsourcing on the Objective Function Value*

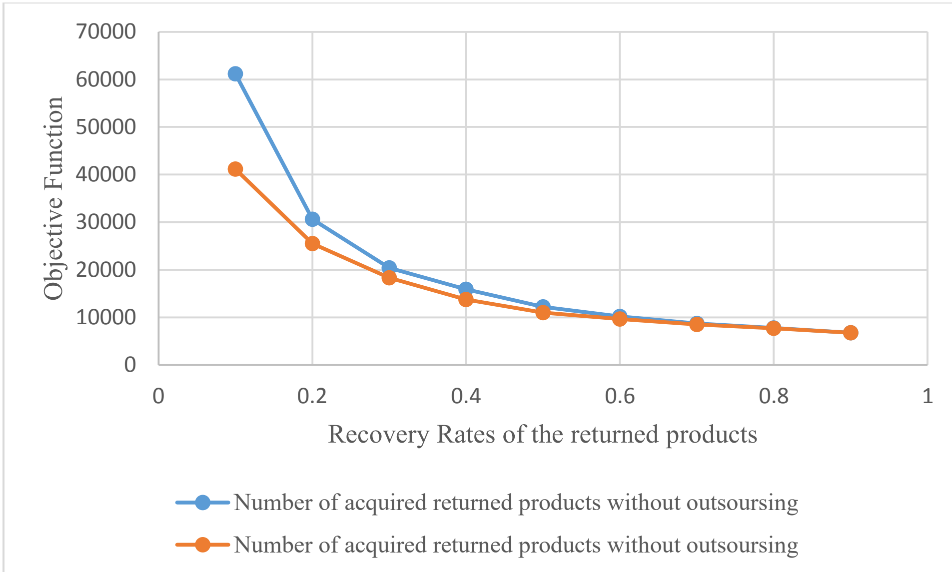

Figure 4-7 *Effect of Outsourcing on the Number of Acquired Returned Products*

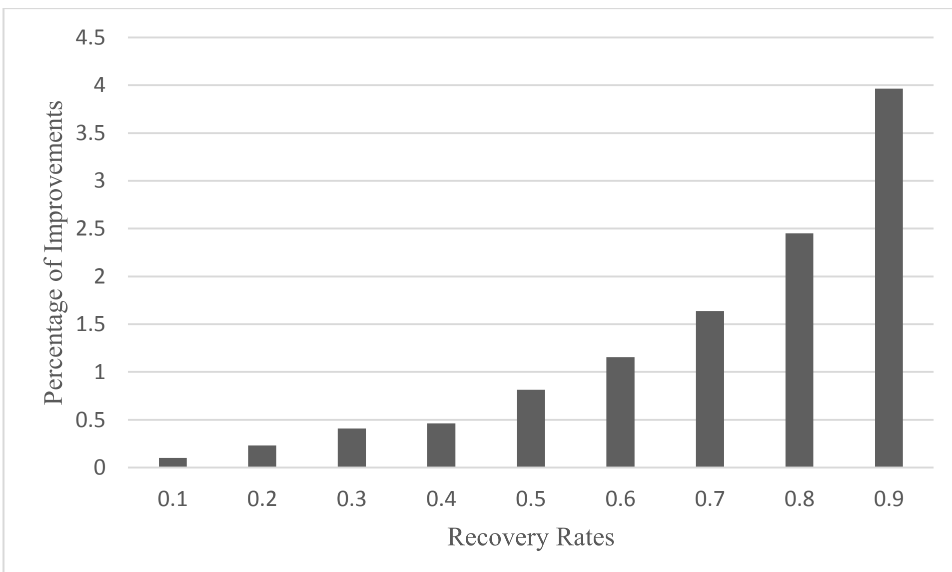

Figure 4-8 *Percentage of Improvements in Objective Function Considering Alternative Routings*

4.6 Summary of the chapter

We have developed a comprehensive mathematical model that integrates production planning of a cellular manufacturing system with the tactical planning of a closed-loop supply chain. The mathematical model proposed in this paper, to the best of our knowledge, is the first model enhancing the cost-effectiveness of cellular manufacturing systems with remanufacturing option by considering alternative process routings and subcontracting the part demands. In this paper, tactical planning of the closed-loop supply chain encompasses several decisions including acquisition of returned product, setup and implementations of disassembly operations, inventory holding of the returned products, remanufacturing of parts having high qualities, and eventually disposal of the returned products that cannot be economically recovered. A commercially available optimization software namely CPLEX is used to solve a large-sized example problem of the mathematical model. Three production policies have been considered in this paper such as internal production, inventory holding, and outsourcing in addition to two manufacturing attributes including alternative process routings and dynamic reconfiguration. Several economic analyses are done to investigate the impacts of different production policies as well as different manufacturing attributes on the mathematical model. The mathematical model in this paper is solved for different instances to investigate the effects of eliminating subcontracting of the part demands, alternative process routings, and dynamic reconfiguration on the objective function value. Results obtained demonstrated that, for all the scenarios, incorporating subcontracting, alternative process routings, and dynamic reconfiguration improve the objective function value. The potential users of this model are the designers of sustainable manufacturing/supply chain systems at the design stage and the managers supervising such enterprises at the operational level.

A sensitivity analysis is also done to find out the effects of recovery rates of the returned products on the objective function value and the number of acquired returned products for each time period. Results showed that alternative process routings and outsourcing reduce the objective function value in all scenarios solved. Since the proposed mathematical model is NP-hard, it is important to derive appropriate solution techniques such as metaheuristics or exact methods such as Benders-decomposition or Lagrangean-relaxation for the future research. Also, incorporating other recovery operations including recycling, refurbishing, and repair would be pursued as the future research of this work.

Chapter 5 A Mathematical Model for Designing a Reliable Cellular Hybrid Manufacturing-Remanufacturing System Considering Alternative and Contingency Process Routings

5.1 Introduction

Design and optimization of a hybrid cellular manufacturing-remanufacturing system in a closed-loop supply chain configuration is presented in this section. Aljuneidi and Bulgak [72, 74] previously proposed a mathematical model for the production planning of a hybrid cellular manufacturing-remanufacturing system. In this paper, machine flexibility of the hybrid manufacturing-remanufacturing system is enhanced using alternative process routings. Alternative process routings can be formed when multi-functional machines and multiple copies of each machine types are existed in the manufacturing system. Hence, each machine type is able to process different operations of a part. Likewise, each process of a part can be implemented on different machine types with different processing times. The mathematical model in this paper considers also one of the important manufacturing attributes namely, contingency process routings for all parts together with the main process routings. Contingency process routings can be utilized when there are machine breakdowns or scheduled maintenance in the main process routings as parts can be re-routed when the main routings are unavailable. By taking contingency process routings into consideration, manufacturing systems can run in a continuous manner [17]. When contingency process routings are selected, production of the other parts types in the main routings are not be affected. Hence, contingency process routings can be used for manufacturing of all the part types. Machines that are selected for the contingency process routings in a time period are completely different entities from the machines in the main process routings in the same time period. According to Figure 5-1, in the forward supply chain, new components are manufactured with the use of raw materials. Remanufactured products are produced with the use of core components of the returned products as well. Accordingly, in the reverse chain, returned products are collected from the customer zones for inspection, classification, and testing in the collection center(s). Returned products are pulled apart in the disassembly center(s) to separate the remanufacturable and reusable components. In the quality control section of the disassembly center, components of the retuned products are classified to two major categories which are "High-quality" and "Low-quality" components. "High-quality" components are the ones with the high recovery rate (i.e. % 80 of the component is recoverable) while the "Low-quality" components are the ones with the low recovery rate (i.e. less than % 10 of the component is recoverable). "High-quality" components are sent to the remanufacturing facilities in which the process of restoring to "like-new" condition is performed. "Low- quality" components are going to be disposed. Remanufacturing usually consists of several stages including disassembly, cleaning, repairing, refurbishing and reassembling. Recognizing the proper manufacturing layout among flow-line production, job-shop production, or cellular manufacturing can highly improve the efficiency of the remanufacturing processes. To achieve sustainability in the manufacturing systems, cellular manufacturing layouts are highly recommended [105]. One of the most essential elements in designing cellular manufacturing systems is the consideration of machine reliability. In the literature review, reliability of the machines is often considered to be 100%. In reality, machines fail during operations. Machine breakdowns are one of the key factors influencing the performance of the system in the operational level due to the causing probable postponements in production planning of the manufacturing system. By taking machine reliability and breakdown effects of the machines to account at the operational level, solutions related to the selection of process routings with lower machine failures lead to reduced overall cost of the cellular manufacturing systems [16, 42]. In this paper, it is assumed that the breakdown time for a machine of type m has an exponential distribution function with the failure rate equal to λ_m. Accordingly, reliability function R (m, t) over the production time t can be written as:

$$R(m, t) = e^{(-\lambda_m t)}$$

Hence, number of the machine breakdowns can be calculated as:

$$N(m, t) = \frac{\text{Total production time}}{\text{Mean time between failures of machine m}}$$

Breakdown cost of the machines can be calculated as:

$$\frac{\text{Total production time}}{\text{Mean time between failures of the machine type m}} * \text{Unit breakdown cost of a machine}$$

Operational cost of the machines can be calculated as:

$$\text{Total production time} * \left(\frac{\text{Mean time to repair of machine type m} + \text{Mean time to failure of machine type m}}{\text{Mean time to failure of the machine type m}}\right) * \text{operational cost of the machine type m}$$

The proposed model considers several manufacturing attributes such as multi-period production settings, reconfigurable layouts of the system, machine duplication, machine investment and machine capacity. There are several parameters pertaining to the reverse supply chain of the model including acquisition of the returned products, disassembly of the returned products, remanufacturing of parts having high qualities, as well as disposition of the returned products that cannot be economically recovered. Figure 5-1 represents the material flow of the proposed hybrid cellular manufacturing-remanufacturing model. When formulating the proposed mathematical model, several assumptions have been taken into consideration as follows:

- The number of cells is constant over the planning horizon and predefined;
- The demand for each part type is deterministic and known in advance in each time period;
- No backlogging is allowed;
- The demand for each part type in each time period can be fulfilled by internal production, and the inventories that can be carried over from the previous time period(s);
- Each machine type has a limited capacity expressed in hours during each time period;
- Reconfiguration involves the addition and removal of the machines to cells and relocation from one cell to another at the beginning of each time period;
- Lot-splitting and dynamic reconfiguration of the cells are considered.

The notations used for the model are presented below followed by the objective function and set of the constraints.

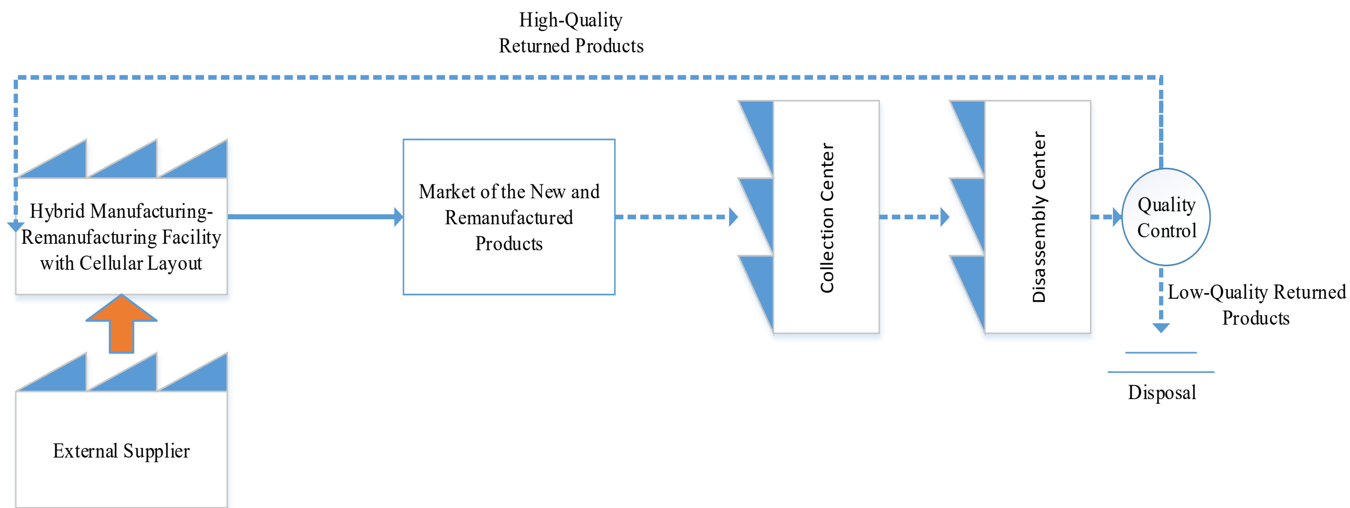

Figure 5-1 *Material flow of the proposed cellular hybrid manufacturing-remanufacturing system*

Problem Sets:

I: Set of part types

M: Set of machines

C: Set of cells

T: Set of time periods

J: Set of returned products

Ξ (I): Set of operation indices of part types

Parameters

D_{it}	Demand of new product i in time period t

D'_{it}	Demand for remanufactured product i in time period t
$t_{\xi im}$	Processing time of operation ξ of new part i on machine m
$t'_{\xi im}$	Processing time of operation ξ of remanufactured part i on machine m
π_m	Time capacity of machine m
α_c	Lower size limit of the cells
β_c	Upper size limit of the cells
R_m	Installation cost of the machine m
K_m	Removal cost of the machine m
M^{∞}	A large positive and integer number
V_{it}	Holding/Carrying cost of new part type i in time period t
V'_{it}	Holding/Carrying cost of remanufactured part type i in time period t
A_m	Machine availability in time period one before procuring any machines

ψ_m	Machine maintenance and overhead costs
ϑ_m	Machine procurement cost
γ_m	Operating cost of machine type m
E_i	Production cost per new part type i
E'_i	Production cost per remanufactured part type i
ω_{jt}	Unit cost to acquire returned product j in time period t
ϕ_{jt}	Setup cost for disassembling returned product j in time period t
μ_{jt}	Unit cost to disassemble returned product j in time period t
λ_{jt}	Unit inventory cost for returned product j in time period t
τ_i	Average recovering rate of part i from all returned products
B_{ij}	Number of parts i contained in product j
$\mathrm{ϝ}_j$	Disposal cost of returned product j

$L_{\xi im}$	If operation ξ of part i can be done on machine type m
$MTBF_m$	Average time between two consecutive failures of machine type m
$MTTR_m$	Average time between two consecutive repairs of machine type m
O_m	Breakdown cost for machine type m

Decision Variables

Y_{mct}^{+}	Number of type m machines added in cell c at the beginning of time period t
Y_{mct}^{-}	Number of type m machines removed from cell c at the beginning of time period t
σ_{mt}	Number of machines of type m procured at time t
$\hat{A}_{mt}$	Quantity of machines type m available at time period t after accounting for machines that have been procured

Q_{it}	Number of new part type i kept in inventory in time period t and carried over to period (t + 1)
Q'_{it}	Number of remanufactured parts i kept in inventory in time period t and carried over to period (t + 1)
d_{jt}	Number of returned product j to be disassembled in time period t
r_{jt}	Number of returned product j to be acquired in time period t
f_{jt}	Number of returned product j in inventory at the end of time period t
δ_{jt}	= 1, if returned product j will be disassembled in time period t, = 0, otherwise
$X_{\xi imct}$	Number of new parts of type i processed by operation ξ on machine m in cell c in time period t on the main routing
$Z_{\xi imct}$	= 1, if operation ξ of part type i is carried out on machine type m in cell c in period t on the main routing, = 0, otherwise

$X'_{\xi imct}$ = 1, number of remanufactured parts of type i processed by operation ξ on machine m in cell c in time period t on the main routing

$Z'_{\xi imct}$ = 1, if operation ξ of remanufactured part type i is carried out on machine type m in cell c in period t on the main routing, = 0, otherwise.

N_{mct} Number of machines of type m presented in cell c at time period t for the main routing

$X''_{\xi imct}$ Number of new parts of type i processed by operation ξ on machine m in cell c in time period t on the contingency routing

$Z''_{\xi imct}$ = 1, if operation ξ of part type i is carried out on machine type m in cell c in period t on the contingency routing.

$X'''_{\xi imct}$ = 1, number of remanufactured parts of type i processed by operation ξ on machine m in cell c in time period t on the contingency routing

$Z'''_{\xi imct}$ = 1, if operation ξ of remanufactured part type i is carried out on machine type m in cell c in

	period t on the contingency routing; = 0, otherwise.
N'_{mct}	Number of machines of type m presented in cell c at time period t for the contingency routing

Objective Function

$$\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{m=1}^{M}(N_{mct} + N'_{mct}) * \psi_m$$

$$+ \sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{m=1}^{M} R_m * Y^{+}_{mct}$$

$$+ \sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{m=1}^{M} K_m * Y^{-}_{mct}$$

$$+\sum_{t=1}^{T}\sum_{i=1}^{I} V_i * Q_{it}$$

$$+\sum_{t=1}^{T}\sum_{i=1}^{I} V'_i * Q'_{it}$$

$$+\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{i=1}^{I}\sum_{\xi=1}^{\Xi} X_{\xi imct} * E_i$$

$$+\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{i=1}^{I}\sum_{\xi=1}^{\Xi} X'_{\xi imct} * E'_i$$

$$+ \sum_{t=1}^{T}\sum_{m=1}^{M} \sigma_{mt} * \vartheta_m$$

$$+ \sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{i=1}^{I}\sum_{\xi=1}^{\Xi-1} X_{\xi imct} * t_{\xi im} * \left(1 + \frac{MTTR_m}{MTBF_m}\right) * \gamma_m$$

$$+\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{i=1}^{I}\sum_{\xi=1}^{\Xi-1} X'_{\xi imct} * t'_{\xi im} * \left(1+\frac{MTTR_m}{MTBF_m}\right) * \gamma_m$$

$$+\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{m=1}^{M}\left(\frac{X_{\xi imct} * t_{\xi im} + X'_{\xi imct} * t'_{\xi im}}{MTBF_m}\right) * O_m$$

$$+\sum_{t=1}^{T}\sum_{j=1}^{J} \omega_{jt} * r_{jt}$$

$$+\sum_{t=1}^{T}\sum_{j=1}^{J} \phi_{jt} * \delta_{jt}$$

$$+\sum_{t=1}^{T}\sum_{j=1}^{J} \mu_{jt} * d_{jt}$$

$$+\sum_{t=1}^{T}\sum_{j=1}^{J} \lambda_{jt} * f_{jt}$$

$$+\sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{j=1}^{J} (1-\tau_i) * f_j * B_{ij} * d_{jt}$$

<u>Subject to:</u>

$$Q_{it-1} + \sum_{m=1}^{M}\sum_{c=1}^{C} X_{\xi imct} - Q_{it} = D_{it};\ \forall\ (\xi, i, t) \qquad 1.1$$

$$Q'_{it-1} + \sum_{m=1}^{M}\sum_{c=1}^{C} X'_{\xi imct} - Q'_{it} = D'_{it};\ \forall\ (\xi, i, t) \qquad 1.2$$

$$Q_{it-1} + \sum_{m=1}^{M}\sum_{c=1}^{C} X''_{\xi imct} - Q_{it} = D_{it};\ \forall\ (\xi, i, t) \qquad 1.3$$

$$Q'_{it-1} + \sum_{m=1}^{M}\sum_{c=1}^{C} X'''_{\xi imct} - Q'_{it} = D'_{it};\ \forall\ (\xi, i, t) \qquad 1.4$$

$$N_{mct} + N'_{mct} = N_{mct-1} + N'_{mct-1}\ Y^{+}_{mct} - Y^{-}_{mct};\ \forall\ (m, c, t) \qquad 1.5$$

$$\alpha_c \leq \sum_{m=1}^{M} N_{mct} + N'_{mct} \leq \beta_c;\ \forall\ (c, t) \qquad 1.6$$

$$\sum_{i=1}^{I}\sum_{\xi=1}^{\Xi} X_{\xi imct}\, t_{\xi im} \leq N_{mct}\, \pi_m;\ \forall\ (m, c, t) \qquad 1.7$$

$$\sum_{\mathrm{i}=1}^{\mathrm{I}}\sum_{\xi=1}^{\Xi} X''_{\xi\mathrm{imct}}\, \mathrm{t}_{\xi\mathrm{im}} \leq N'_{\mathrm{mct}}\, \pi_m; \forall\ (\mathrm{m, c, t}) \quad 1.8$$

$$\sum_{\mathrm{i}=1}^{\mathrm{I}}\sum_{\xi=1}^{\Xi} X'_{\xi\mathrm{imct}}\, t'_{\xi\mathrm{im}} \leq \mathrm{N}_{\mathrm{mct}}\, \pi_m; \forall\ (\mathrm{m, c, t}) \quad 1.9$$

$$\sum_{\mathrm{i}=1}^{\mathrm{I}}\sum_{\xi=1}^{\Xi} X'''_{\xi\mathrm{imct}}\, t'_{\xi\mathrm{im}} \leq N'_{\mathrm{mct}}\, \pi_m; \forall\ (\mathrm{m, c, t}) \quad 1.10$$

$$\widehat{\mathrm{A}}_{\mathrm{m(t=1)}} = \mathrm{A}_{\mathrm{m(t=1)}} + \sigma_{\mathrm{m(t=1)}}; \forall\ (\mathrm{m}) \quad 1.11$$

$$\widehat{\mathrm{A}}_{\mathrm{m(t+1)}} = \widehat{\mathrm{A}}_{\mathrm{mt}} + \sigma_{\mathrm{m(t+1)}}; \forall\ (\mathrm{m}) \quad 1.12$$

$$\sum_{\mathrm{c}=1}^{\mathrm{C}} \mathrm{N}_{\mathrm{mct}} + N'_{\mathrm{mct}} = \widehat{\mathrm{A}}_{\mathrm{mt}}; \forall\ (\mathrm{m, t}) \quad 1.13$$

$$X_{\xi imct} \leq \mathrm{M}Z_{\xi imct}; \forall\ (\xi, \mathrm{i, m, c, t}) \quad 1.14$$

$$X'_{\xi imct} \leq \mathrm{M}Z'_{\xi imct}; \forall\ (\xi, \mathrm{i, m, c, t}) \quad 1.15$$

$$X''_{\xi imct} \leq \mathrm{M}Z''_{\xi imct}; \forall\ (\xi, \mathrm{i, m, c, t}) \quad 1.16$$

$$X'''_{\xi imct} \leq \mathrm{M}Z'''_{\xi imct}; \forall\ (\xi, \mathrm{i, m, c, t}) \quad 1.17$$

$$\mathrm{f}_{\mathrm{jt}} + \mathrm{d}_{\mathrm{jt}} - \mathrm{f}_{\mathrm{jt}-1} = \mathrm{r}_{\mathrm{jt}}; \forall\ (\mathrm{j, t}) \quad 1.18$$

$$\mathrm{d}_{\mathrm{jt}} \leq \mathrm{M}\delta_{\mathrm{jt}}; \forall\ (\mathrm{j, t}) \quad 1.19$$

$$\sum_{m=1}^{M}\sum_{c=1}^{C} X'_{\xi imct} \leq \tau_{\mathrm{i}} \sum_{\mathrm{j}=1}^{\mathrm{J}} \mathrm{B}_{\mathrm{ij}}\, \mathrm{d}_{\mathrm{jt}}; \forall\ (\mathrm{j, t}) \quad 1.20$$

$$\sum_{m=1}^{M}\sum_{c=1}^{C} X'''_{\xi imct} \leq \tau_{\mathrm{i}} \sum_{\mathrm{j}=1}^{\mathrm{J}} \mathrm{B}_{\mathrm{ij}}\, \mathrm{d}_{\mathrm{jt}}; \forall\ (\mathrm{j, t}) \quad 1.21$$

$$Z_{\xi imct} \leq L_{\xi im}; \forall\ (\xi, \mathrm{i, m, c, t}) \quad 1.22$$

$Z'_{\xi imct} \leq L_{\xi im}$; ∀ (ξ, i, m, c, t) 1.23

$Z''_{\xi imct} \leq L_{\xi im}$; ∀ (ξ, i, m, c, t) 1.24

$Z'''_{\xi imct} \leq L_{\xi im}$; ∀ (ξ, i, m, c, t) 1.25

$\sum_{m=1}^{M} \sum_{c=1}^{C} X_{\xi+1mct} = \sum_{m=1}^{M} \sum_{c=1}^{C} X_{\xi mct}$; ∀ (ξ, i, t) 1.26

$\sum_{m=1}^{M} \sum_{c=1}^{C} X'_{\xi+1mct} = \sum_{m=1}^{M} \sum_{c=1}^{C} X'_{\xi mct}$; ∀ (ξ, i, t) 1.27

$\sum_{m=1}^{M} \sum_{c=1}^{C} X''_{\xi+1mct} = \sum_{m=1}^{M} \sum_{c=1}^{C} X''_{\xi mct}$; ∀ (ξ, i, t) 1.28

$\sum_{m=1}^{M} \sum_{c=1}^{C} X'''_{\xi+1mct} = \sum_{m=1}^{M} \sum_{c=1}^{C} X'''_{\xi mct}$; ∀ (ξ, i, t) 1.29

N'_{mct}, N_{mct} Y^{+}_{mct}, $Y^{-}_{mct} \geq 0$ and integer; ∀ (m, c, t) 1.30

Q_{it}, $Q'_{it} \geq 0$ and integer; ∀ (i, t) 1.31

$X_{\xi imct}$,$X''_{\xi imct}$, $X'_{\xi imct}$, $X'''_{\xi imct} \geq 0$; ∀ (ξ, i, m, c, t) and integer 1.32

σ_{mt}, $\widehat{A}_{mt} \geq 0$ and integer; ∀ (m, t) 1.33

$Z_{\xi imct}$, Z'_{zzimct}, $Z''_{\xi imct}$, $Z'''_{\xi imct} \in \{0, 1\}$; ∀ (i, m, c, t) 1.34

Model objective Function: The objective function of the model consists of several cost terms. The first term shows the maintenance and overhead costs of the machines involved in main and contingency routings. The second term demonstrates the cost of the machine installations while the third term represents the cost of the machine removals. The fourth term is pertinent to the inventory carrying cost of the parts for manufacturing new products. The fifth term is pertinent to the inventory carrying cost of the parts for remanufacturing returned products. The sixth term is relevant to the production cost of the new components. The seventh term is related to the production cost of the remanufactured components. The eighth term represents machines procurement cost. The ninth term demonstrates machine operating cost for producing new components. The tenth term shows machine operating cost for producing remanufactured components. The eleventh term shows the machine breakdown cost. The twelfth term represents acquiring cost of the returned products. The thirteenth term represents the setup cost for disassembling operations. The fourteenth term addresses the disassembling costs of the returned products. The fifteenth term shows the inventory holding costs for returned products, and the last term, term number sixteen, addresses the disposal cost of the returned products.

Model Constraints: The objective function of the model is subjected to constraints as follows: Constraint (1.1) demonstrates that the demands for a new part type i in each time period can be fulfilled by internal production, and/or the inventory that can carried over from previous time period subtracting the inventory of the current time period in the main routing. Constraint (1.2) shows that the demands of a remanufactured part type i in each time period can be fulfilled by internal production, and/or the inventory that can carried over from previous time period subtracting the inventory of the current time period in the main routing. Constraint (1.3) demonstrates that the demands for a new part type i in each time period can be fulfilled by internal production, and/or the inventory that can carried over from previous time period subtracting the inventory of the current time period in the contingency routing. Constraint (1.4) shows that the demands for of a remanufactured part type i in each time period can be fulfilled by internal production, and/or the inventory that can carried over from previous time period subtracting the inventory of the current time period in the contingency routing.

Constraint (1.5) demonstrates the reconfigurability of the manufacturing system where the number of machines of type m at the beginning of each time period is equal to number of machines of type m in the previous time period considering installations and removals of the machines of type m in the cell c at the beginning of each time period. Constraint (1.5) ensures that machines can be chosen from the set of available machines in each time period to form the main or contingency routings. For example, a machine that was used in a period as part of a contingency routing, is available for the next period to be used either in contingency or main process routings. Constraint (1.5) also ensures that within a period, machines allocated for the main routing will not be used for the contingency routing. The size of the cells is user-defined through constraint (1.6) where the number of machine assignments of each type should be lied between the lower size and upper size of the cells. Constraint (1.7) ensures that the capacity of machines would not be exceeded for producing new components in the main routing. Constraint (1.8) ensures that the capacity of machines would not be exceeded for producing new components in the contingency routing. Constraint (1.9) ensures that the capacity of machines would not be exceeded for producing remanufactured components in the main routing. Constraint (1.10) ensures that the capacity of machines would not be exceeded for producing remanufactured components in the contingency routing. Constraint (1.11) is relevant to the availability of machines for time period 1 taking into consideration the machine procurements option. The total number of machines of each type available in the system is equal to the machine availability before machine procurements in addition to the number of machines acquired in the first time-period. Constraint (1.12) indicates that machine availabilities for the subsequent time periods excluding time period 1 can be recorded. The number of machine procurements in the current time period along with the number of machines that have been acquired in all the preceding time periods demonstrates total available machines in the system. Constraint (1.13) states that the total number of machines in each cell in both main routing and contingency routing should not exceed the total number of available machines. Constraint (1.14) indicates that the number of new parts produced can be positive only if $Z_{\zeta imct}$ = 1, that is, it has been decided that part i would be produced by operation ζ on machine m in cell c in time period t in the main routing. Constraint (1.15) indicates that the number of remanufactured parts produced can be positive only if $ZR_{\zeta imct}$ = 1, that is, it has been decided that remanufactured part i would be produced by operation ζ on machine m in cell c in time period t. Constraint (1.16) indicates that the number of new parts produced can be positive only if $ZP_{\zeta imct}$ = 1, that is, it has been decided that part i would be produced by operation ζ on machine m in cell c in time period t in the contingency routing. Constraint (1.17) indicates that the number of parts produced can be positive only if $ZPR_{\zeta imct}$ = 1, that is, it has been decided that remanufactured part i would be produced by operation ζ on machine m in cell c in time period t in the contingency routing. Constraint (1.18) shows that the total number of returned products to be acquired can be calculated through the summation of total number of returned products to be kept in inventory for the current time period as well as total number of returned products to be disassembled for the current time period subtracting the amounts of inventory carried over from the previous time period. Constraint (1.19) indicates a logical constraint for disassembling activities. Constraint (1.20) takes to account the quality levels of the returned products. It represents the quantity of parts acquired from returned products is dependent to their quality levels in the main routing. Constraint

(1.21) takes to account the the quality levels of the returned products. It represents the quantity of parts acquired from returned products is dependent to their quality levels in the contingency routing. Constraints (1.22-1.25) ensures that each operation of a part either for the new components or remanufactured components is assigned to appropriate machines according to the part-machine incidence matrix in both main and contingency routings. Constraints (1.26-1.29) show the material flow conservation of the new and remanufactured parts under production in both main and contingency process routings. This set of constraints ensures that the total quantity of parts processed in an operation is equal to the total number of parts in the next/preceding operation. Constraints (1.26-1.29) also allow for exploration of more allocations of the part routings. Constraint (1.30), Constraint (1.31), Constraint (1.32), Constraint (1.33) and Constraint (1.34) specify the logical binary and non-negativity integer requirements on the decision variables.

5.2 Numerical Example

A number of example problems are solved with the use of CPLEX, a commercially available software. For the clarification purposes, one example problem is explained in detail to show the applications of the proposed model in designing a cellular hybrid manufacturing-remanufacturing system.

5.2.1 Example 1

In solving example 1, there are 2 components, 2 machines, 2 cells and 2 planning periods that have been considered. Also, in the reverse supply chain side of the model, there are 2 returned products that need to be collected from the customer zones.

5.2.2 Input data and problem size

The input data of this example is given in Table 5-1. The input data are based on the work by Aljuneidi and Bulgak [74]. Table 2 shows the size of the Example 1. Accordingly, there are 924 constraints as well as 704 integer variables.

Table 5-1 Input data for Example 1

Parameter	Value
Demand for new part type i at time period t	200-600
Demand for remanufactured part type i at time period t	100-300
Processing time of operation ξ of new part type i on machine m (seconds)	4-8
Processing time of operation ξ of remanufactured part type i on machine m (seconds)	2-4
Production cost per new part type i	200-300
Production cost per remanufactured part type i	100-150
Inventory holding cost per new part type i per time period	8-10
Inventory holding cost per remanufactured part type i per time period	5
Quantity of machine type m available at time period t	6
Capacity of one unit of machine type m during one-time period	1500
Operating cost per unit time per machine type m	10
Maintenance and overhead costs per machine type m	20
Procurement cost per machine type m	500-700
Machine Installation cost	10
Machine Removal Cost	8
Upper limit cell size	20
Lower limit cell size	3
Acquiring cost of the returned product j in time period t	1-3
Setup cost for disassembling returned product j in time period t	2-3

Table 5-1 continued

Parameter	Value
Inventory cost for returned product j in time period t	4-5
Disassembly cost of returned product j in time period t	2-3
Average recovering rate of returned product j	0.9
Number of part i contained in product j	9-13
Disposal cost of the returned product j	60-70
Breakdown cost for machine type m	1200-1800
Average time between two consecutive failures of machine type m (hour)	3-8
Average time between two consecutive repairs of machine type m (hour)	51-90

Table 5-2 Generic attributes of the Example 1

No. of parts	No. of machines	No. of cells	No. of retuned products	No. of operations	No. of binary variables	No. of integer variables	No. of constraints
2	2	2	2	5	324	704	924

5.2.3 Solution of the Example 1

The main alternative process routings and contingency alternative process routings of the new parts and remanufactured parts are brought in Tables 5-3 to 5-6. In Table 5-3, main process routings of the new parts are shown. According to Table 5-3, operation 2 of part type 1, for example, can be performed on machine type 1 in 2 different cells. Table 5-4 demonstrates the contingency process routings for producing remanufactured parts. Accordingly, operation 4 of part type 1 can be done on machine 1 and 2 in cell 1 in time period 1. Noteworthy, the main routing for the operation 4 of part type 1 in period 1 is the use of machine 1 in cell 2 with respect to Table 5-3. According to Table 5-4, operation 4 of part type 1 can be done on machine 1 and machine 2 through the use of 2 different cells in case of unavailability of the main routing. According to Table 5-3, operation 4 of part type 1 is performed in the main routing on machine 1 in cell 2.

Table 5-5 shows the main process routings for producing remanufactured products. Table 5-6 also demonstrates contingency process routings for the remanufactured products. According to Table 5-5, operation 1 of part type 2 is performed on machine type 2 in cell 1. However, in case of unavailability of the main routing due to the machine breakdowns for operation 1 of part type 2 in time period 2, re-routing will be implemented. Hence, operation 1 of part type 2 in time period 2 can be done on machine type 2 in cell 2 with respect to the Table5-6. According to Table 5-5, operation 3 of part type 1 is performed in cell 2 with the use of machine type 1. Re-routing of the operation 3 of part type 1 in time period 1 can be done in case of having unavailability in the main routing. Hence, regarding the table 5-6, operation 3 of part type 1 can be done on machine type 1 in cell 1.

Table 5-3 Main routings for new parts

Operations/Part	Time Period	1	2	3	4	5
1	1	377 M2/C2	377 M1/C2	377 M1/C1	377 M1/C2	124 M2/C1 253 M2/C2
	2	423 M2/C1	339 M1/C1 84 M1/C2	423 M1/C2	423 M1/C1	375 M2/C2 48 M2/C1
2	1	464 M1/C1	464 M2/C1	464 M2/C2	443 M1/C2 21 M1/C1	464 M1/C1
	2	436 M1/C1	436 M2/C1	436 M2/C1	436 M1/C1	436 M1/C1

Table 5-4 Contingency routings for new parts

Operations/Part	Time Period	1	2	3	4	5
1	1	377 M2/C2	149 M1/C1 228 M1/C2	377 M2/C1	326 M1/C2 51 M2/C2	377 M2/C2
	2	423 M2/C2	423 M1/C2	423 M2/C2	298 M1/C1 32 M1/C2 93 M2/C2	375 M2/C1 48 M2/C2
2	1	464 M1/C1	464 M2/C2	434 M2/C2 30 M2/C1	464 M1/C1	464 M2/C1
	2	436 M1/C2	436 M2/C2	436 M2/C2	436 M1/C2	436 M2/C2

Table 5-5 Main routings for remanufactured parts

Operations/Part	Time Period	1	2	3	4	5
1	1	107 M1/C1	107 M1/C2	107 M1/C2	107 M1/C2	107 M2/C2
	2	243 M1/C1	243 M1/C1	243 M1/C1	243 M1/C2	243 M2/C1
2	1	253 M2/C1	253 M1/C2	253 M1/C2	253 M1/C2	253 M1/C2
	2	297 M2/C1	297 M1/C1	297 M1/C1	297 M1/C1	297 M1/C1

Table 5-6 Contingency routings for remanufactured parts

Operations/Part	Time Period	1	2	3	4	5
1	1	107 M2/C1	107 M1/C2	107 M1/C1	107 M2/C1	107 M2/C1
	2	243 M2/C1	243 M1/C1	243 M1/C1	243 M1/C2	243 M2/C1
2	1	253 M2/C1	253 M2/C1	253 M1/C1	253 M1/C1	253 M2/C1
	2	297 M2/C2	297 M1/C2	297 M2/C2	276 M1/C2 21 M1/C1	297 M1/C2

Table 5-7 demonstrates the amount of inventory that needs to be kept in time period 1 for carrying it over to time period 2 for the new and remanufactured parts.

Table 5-7 Quantities of the inventory that needs to be kept

Part	Time period	Value for the new parts	Value for the remanufactured parts
1	1	177	7
1	2	0	0
2	1	164	3
2	2	0	0

According to Kusiak [114], resorting to alternative process routings decreases the total number of available machines in the system. Table 5-8 shows the number of machines in the system with the assumption of considering and eliminating alternative process routings. Accordingly, when machines are multi-functional and resorting to alternative process routings is available for the manufacturing systems there are 64 machines in the system. However, with the assumption of eliminating alternative process routings there are 74 machines in the system. Table 5-8 also shows when alternative process routing is eliminated from the mathematical model, objective function value is increased from 3,333,489 to 3,636,369 which shows 302,880 in the objective function value. Accordingly, resorting to contingency process routings impose a negligible increasing effect on the objective function value. According to Table 5-8, when contingency process routing is eliminated from the mathematical model 0.019% of the total costs is saved. Hence, objective function value is decreased from 3,333,489 to 3,332,851 by eliminating contingency process routings. This shows the efficiency of the proposed contingency routings in the mathematical model. Contingency process routings not only improve the efficiency and reliability of the system, but also impose an insignificant cost increases in the objective function value. Production managers dealing with designing reliable cellular manufacturing systems can resort to the advantages contained in the use of contingency process routings.

Table 5-8 Number of machines in the system

		Objective-Function value	Objective function with the elimination of contingency routings	Percentage of increase
Number of Machines with Alternative Routings	64	3,333,489	3,332,851	0.019%
Number of Machines without Alternative Routings	74	3,636,369		

Table 9-10 demonstrate the allocation of machines to cells in 2 time periods for the main and contingency process routings. According to Table 5-9, for example, there is a need for 8 machines of type 1 in cell 1 in the second time period. In Table 5-10, for instance, there is a need for 5 machines of type 1 in cell 2 in the second time period. It is worth noting, the summation of the number of machines for a part type in a time period through the main and contingency process routings do not violate the upper limit cell size which is 20 machines. For example, the summation of the number of machines 1 in cell 1 and 2 in time period 1 in the main and contingency process routings is 19 which is less than 20.

Table 5-9 Allocation and quantity of machine types for the main routing

Machines	Cells	Time periods	Value
1	1	1	5
1	1	2	8
1	2	1	5
1	2	2	2
2	1	1	2
2	1	2	4
2	2	1	4
2	2	2	2

Table 5-10 Allocation and quantity of machine types for the contingency routing

Machines	Cells	Time periods	Value
1	1	1	4
1	1	2	1
1	2	1	2
1	2	2	5
2	1	1	4
2	1	2	2
2	2	1	6
2	2	2	8

Table 5-11 shows the quantities of the returned products and obtained components. Table 5-11 also shows the quantities of the returned products to be disassembled, quantities of the returned products that need to be kept in inventory as well as the values corresponding to the binary variable of the setup for disassembly operations. According to Table 5-11, there is a need to collect 22 returned products 1 from the customer zones in time period 1. However, in time period 2 there is a need for 24 returned product 1. Accordingly, there is no need for collecting returned product 2 in time period 1, but there is a need for the collection of 2 returned product 2 in time period 2. According to Table 5-11, the quantity of the returned products in disassembly center is completely equivalent with the acquired quantity of the returned products for different time periods. The quantity of the returned products in the storage is 0 with respect to Table 5-11. Accordingly, the system is set up to perform the disassembly operations for the returned product 1 in time period 1 and time period 2 as well as for the returned product 2 in the second time period.

Table 5-11 Retuned products quantities

Returned Product	Time period	Acquired Quantity	Quantity in Diss. Ass. Center	Quantity in Inventory	Setup for Diss. Operations
1	1	22	22	0	1
1	2	24	24	0	1
2	1	0	0	0	0
2	2	2	2	0	1

5.3 Computational experiments

To further illustrate the proposed model, we solved the mathematical model for seven other scenarios. According to Table 5-12, all the scenarios are solved with the use of IBM ILOG CPLEX Optimization Studio 12.7/OPL. For all the scenarios, number of part types, number of machines, number of cells, and number of returned products are reported. Number of constraints as well as the number of decision variables for each scenario is reported. The solution time is the major criterion for testing the solving ability of CPLEX. Seven scenarios are compared based on the computational times and the objective function value. For each scenario, the effect of the elimination of alternative process routings and constringency process routings on the objective function value has been investigated in Table 5-13. The percentage of cost savings after the elimination of alternative routings can be calculated as: 100*(objective function value without alternative routings – objective function with alternative process routings). Likewise, the cost savings related to the elimination of contingency process routings can be calculated as: 100*(objective function value with contingency routings – objective function value without contingency process routings). According to Table 12, both solution times and objective function value are increased while increasing the scenario sizes. Scenario 1 can be solved within less than a minute. However, from scenario 2 the solution time is increased until the scenario 5 which takes 13 minutes to be solved. Based on our previous observations of the cellular manufacturing systems and with respect to the literature review, scenario 6 can be considered as a real-size instance of the mathematical model with 43,848 variables and 47,832 constraints. Scenario 6 can be solved in 47 minutes which shows a reasonable computational time. Scenario 7 is a large-scale instance of the mathematical model which cannot be solved in polynomial time by having 182,250 decision variables as well as 189,340 constraints. According to Table 5-13, with elimination of alternative process routings, 1.42% of the total costs can be saved. The maximum cost saving is relevant to the scenario 6 with 2.94% and the minimum cost saving is pertinent to the scenario 1 with 0.88%. According to Table 5-13, removing contingency process routings has a very negligible effect on the total costs which shows the efficiency contained in designing contingency routings. Resorting to contingency process routings can increase the reliability and flexibility of the manufacturing systems against demand changes or machine breakdowns. According to Table 5-13, removing contingency process routings can only decrease the total costs by 0.013%. Accordingly, the maximum cost saving is related to the scenario 1 with 0.019% and the minimum cost saving is related to scenario 3 with 0.009%.

Table 5-12 Different problem scenarios

Problem Scenario	Number of component types	Number of time periods	Number of Operations	Number of machine types	Number of products	Number of cells	Number of variables	Number of Constraints	Solution Time (Seconds)	Objective Function
1	2	2	5-9	2	2	4	1,376	1,612	28	3,333,494
2	2	3	5-9	3	2	2	2,322	2,700	89	4,160,333
3	4	3	5-9	3	3	3	7,962	9,312	194	17,249,057
4	4	3	5-9	3	3	5	13,218	14,598	363	17,282,646
5	4	6	5-9	3	3	3	15,924	18,624	767	33,809,026
6	5	6	5-9	5	2	4	43,848	47,832	2,775	40,786,386
7	5	10	5-9	5	2	10	182,250	189,340	N. A	N. A

Table 5-13 Solution analyses for different problem scenarios

Problem Scenario	Objective Function without alternative routings	Percentage of cost saving by adding alternative process routings	Objective function without contingency routings	Percentage of cost saving with the elimination of contingency process routings
1	3,636,348	0.88	3,332,851	0.019
2	4,206,909	1.11	4,159,661	0.016
3	17,462,365	1.22	17,247,403	0.009
4	17,492,411	1.19	17,279,629	0.017
5	34,214,755	1.18	33,805,432	0.01
6	42,024,113	2.94	40,781,506	0.011
7	N. A	N. A	N. A	N. A
Average		1.42		0.013

5.4 Summary of the Chapter

In spite of the growing research interest in the design of the sustainable closed-loop supply chains, sustainability criteria in the design of manufacturing systems has absorbed less attention. In order to build a sustainable manufacturing enterprise incorporating the manufacturing system and its closed-loop supply chain, we presented a mixed integer programming model for the design of a hybrid cellular manufacturing-remanufacturing model. This is, to the best of author's knowledge, the first integrated model in the design of hybrid cellular manufacturing systems which considers alternative process routings and contingency process routings to enhance the flexibility and reliability of the manufacturing system. Several activities are considered in the closed-loop supply chain of the model including setup for disassembly of the returned products, disassembly of the returned products, remanufacturing of the returned products with the "high-quality" levels, and the disposal of the "low-quality" returned products. In the manufacturing system, the main activities are assigning machines to cells and assigning operations of each product to different machines in a cellular hybrid manufacturing-remanufacturing system. The objective function of the model is to minimize the total costs incorporating total costs related to the tactical planning of the closed-loop supply chain and costs related to the operational planning of the hybrid cellular manufacturing-remanufacturing system. The future work in this research will be the development of appropriate solution techniques with the use of metaheuristics or exact methods such as Benders-decomposition or Lagrangian-relaxation. Considering stochastic parameters is another research direction that would be perused for the future research.

Chapter 6 A chance-constrained two-stage stochastic programming model for designing a cellular remanufacturing in a closed-loop supply chain: A queuing-based approach

6.1 Introduction

In this chapter, a chance-constrained stochastic cellular manufacturing system is formulated as a queuing system which takes the reliability of the machines into account. For applying queueing theory in the cell formation problem, parts and machines are considered as customers and servers, respectively. The queuing system in this paper is assumed to be M /M / 1, where the arrival rates of the parts (λ) and the service rates of the machines (μ) are uncertain and described by exponential distribution. In this queuing system each machine processes different part types in which each part type has a different arrival rate. The minimum of several exponentially distributed variables with the arrival rates of $\lambda_1, \lambda_2, \ldots \lambda_m$ is also exponential with the arrival rate of $\lambda = \sum_{i=1}^{m} \lambda_i$. Therefore, the utilization rate of each machine can be calculated as $\rho = \frac{\sum_{i=1}^{m} \lambda_i}{\mu}$. In a M /M / 1 queue system, each machine can process at most one part at a time. Hence, there is a queue behind of each machine. The population in the queuing system follows birth and death process, that is, the population increase with an arrival (birth) and the population decrease with a departure (death). The time that each part spends in cells encompasses both of the queue time and service time. To evaluate the quantities of work-in-process and utilizations of machines, an *open* Jackson network is considered in this paper. An *open* Jackson network is consisted of J nodes where each arrival from outside is independently routed to node j with probability $P_{0j} \geq 0$ and $\sum_{j=1}^{J} P_{0j} = 1$. Upon service completion at node i, a job may go to another node j with probability P_{ij} or leave the network with probability $P_{i0} = 1 - \sum_{j=1}^{J} P_{ij}$. In this paper, a node stands for a machine. Hence the overall arrival rate to machine i can be calculated as discussed by Boucherie and Van Dijk [114]:

$$\lambda_i = \alpha\, P_{0i} + \sum_{j=1}^{J} \lambda_i\, P_{ji};\ \forall\ (i) \tag{1}$$

In Eq. (1), α is considered to be the arrival rate of the parts from outside following a poison distribution.

Theorem: In a Jackson network with the assumptions mentioned earlier in which all the stations have unlimited capacity, the following equilibrium is always valid [114]:

$$\pi_{\mathrm{n1,n2,\ldots nj}} = \prod_{j=1}^{J} \pi_j\, n_j = \prod_{j=1}^{J} (1 - \rho_j)\, \rho_j^{n_j} \tag{2}$$

Again, ρ can be calculated with the use of $\frac{\sum_{i=1}^{m} \lambda_i}{\mu}$. $\pi_{n_j}^{(j)}$ is assumed to be the probability of being n_j parts in the queue of machine j. $\pi_{\mathrm{n1,n2,\ldots nk}}$ is the probability of having n_1 jobs in the queue of parts behind machine 1, n_2 jobs in the queue of parts behind machine 2, …, and n_j jobs in the queue of parts behind machine j.

Eq. (2) shows the probability mass function of K independent geometric random variables. Hence, this network can be decomposed to K dependent M/ M/ 1 queuing system. According to Boucherie and Van Dijk [114], average number of jobs behind each machine can be calculated as follows [114]:

$$L_j = \frac{\rho_j}{1 - \rho_j}\ \forall\ (j) \tag{3}$$

We assume that if the summation of queue time and service time violates a predefined critical waiting time, parts are going to be damaged. For example, in the manufacturing processes of prepreg carbon fibres which have a certain shelf-time, optimizing the waiting time in the system is very important. Another example could be in the products in which epoxy resins are used in the manufacturing processes. Hot and cold shrinking-fittings are usually considered as the manufacturing processes in which waiting time in the system needs to be optimized. Hence, to avoid a long waiting time of the parts in the queuing system, a chance-constrained is added to the mathematical model. Accordingly, the probability that the waiting time of the parts in the system exceeds the critical waiting is less than the service level (Ξ). Figure 6-1 demonstrates the arrangement of the machines in the cells and the queue of the parts behind of each machine in a cellular manufacturing system. One of the most essential elements in designing a stochastic cellular manufacturing system is the consideration of machine reliability. The proposed mathematical model integrates the significant manufacturing attributes including machine breakdown influence in terms of machine overhaul cost and production time loss in the calculation of the machine operational cost to incorporate reliability engineering aspects in the model. The reliability of the machines is considered through concepts such as mean time to failures (MTTF) and mean time to repairs (MTTR) for each machine. The cellular manufacturing system in this paper is configured as a part of a sustainable closed-loop supply chain in which the processes of collecting, disassembling, and remanufacturing of the returned products in the facilities with the cellular layout occur in a closed-loop configuration. According to Figure 4-2, returned products are remanufactured to fulfil the demands of customers. Accordingly, in the reverse chain, returned products are collected in the collection centres from the customer zones to be inspected and tested in the disassembly centres. Hence, returned products are pulled apart to separate all the re-manufacturable components. After the quality-control inspections, high-quality components are shipped to remanufacturing centres with the cellular layout in which the process of restoring returned products to "like-new" conditions are performed. Low-quality components are going to be disposed.

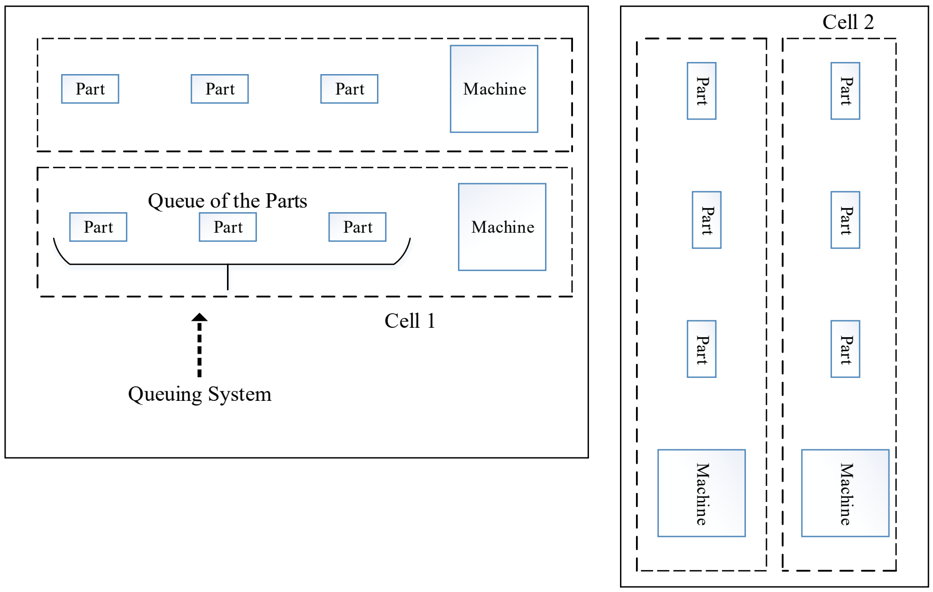

Figure 6-1 *Example of the queuing system*

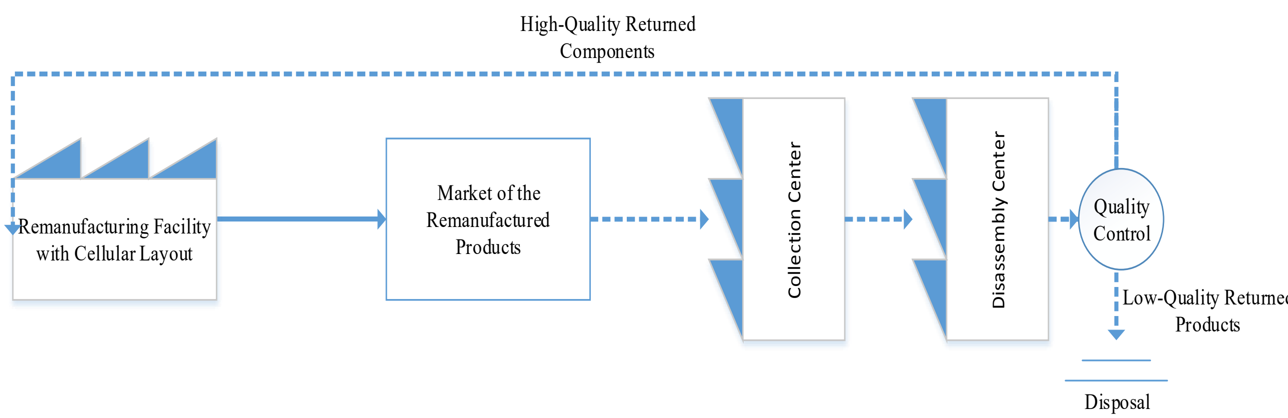

Figure 6-2 *Material flow for the proposed chance-constrained stochastic cellular manufacturing system in a closed-loop supply chain*

6.2 Model Assumptions

When formulating the proposed mathematical model, several specific assumptions have been taken into account as follows:

- Two-stage stochastic optimization is used to formulate the mathematical model;
- The number of cells is constant and predefined in all the scenarios;
- The demand for each part type is stochastic and is described by a set of scenarios;
- The demand for each part type in each scenario can be fulfilled by internal production and outsourcing;
- Outsourcing cost is stochastic and is described for the different scenarios.
- Each machine type has a limited capacity expressed in hours;
- Machine breakdown (repair) cost is known and constant in all the scenarios;
- Machine maintenance and overhead cost is known and constant in all the scenarios.

6.2.1 Model parameters and decision variables

The notations used in the model are presented below followed by the objective function and set of constraints.

Problem Sets

I: Index set of part types

M: Index set of machines

C: Index set of cells

J: index set of returned products

S: Index set of scenarios

Parameters

D_i^s	Demand of part i in scenario s
E_i	Production cost per unit of part i
W_i	Inter-cell material handling cost per part type i
t_{im}	Processing time of part i on machine m
M^{∞}	A large positive and integer number
σ_m	Maintenance and over-head cost of machine m
ς_m	Procurement cost of machine m
β_m	Operating cost of machine m
μ_m	Capacity of machine m
L_c	Lower size limit of the cell c
U_c	Upper size limit of the cell c
ξ_i	Average recovering rate of part i
Υ_{im}	If part i can be processed on machine m
O_i^s	Outsourcing cost of part i in scenario s
B_{ji}	Number of components i contained in product j
Φ_j	Unit cost to acquire returned product j
κ_j	Setup cost for disassembling returned product j
τ_j	Unit cost to disassemble returned product j
χ_j	Disposal cost of returned product j
$MTBF_m$	Average time between two consecutive failures of machine type m
$MTTR_m$	Average time between two consecutive repairs of machine type m
Ч$_m$	Breakdown cost of the machine type m
P_s	Probability of scenario s occurs
Ξ	Service level
σ_{system}	Average time that each part spends in the system

Ψ	Critical waiting time

Decision Variables

First-stage decision variables

N_{mc}	Number of type m machines presented in cell c
ζ_m	Number of machine type m that are purchased
d_j	Number of returned product j to be disassembled
r_j	Number of returned product j to be acquired
δ_j	= 1, if returned product j is disassembled; = 0 otherwise
ρ_m	Utilization rate of machine m
α_{mc}	= 1, If machine type m is assigned in cell c; = 0 otherwise
X_{ic}	= 1, if part type i is processed in cell c; = 0 otherwise

Second-stage decision variables

λ_{imc}^{s}	Arrival rate of part i on machine type m in cell c in scenario s
Z_{imc}^{s}	= 1, if part type i is processed on machine type m in cell c in scenario s; = 0 otherwise
Q_i^s	Number of outsourced parts i in scenario s

Objective Function

Minimize

$\sum_{s=1}^{S} P_s$ [$\sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{c=1}^{C} t_{im} * \lambda_{imc}^{s} * \beta_m * (1 + \frac{MTTR_m}{MTBF_m}) + \sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{c=1}^{C} t_{im} * \frac{\lambda_{imc}^{s}}{MTBF_m} *$ Ч$_m$ * +
$\sum_{i=1}^{I} O_i^s * Q_i^s + \sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{c=1}^{C} E_i * \lambda_{imc}^{s}$] + $\sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{c=1}^{C} W_i * \Upsilon_{im} * X_{ic} * (1 - \alpha_{mc})$ +
$\sum_{m=1}^{M}\sum_{c=1}^{C} \sigma_m * N_{mc} + \sum_{m=1}^{M} \varsigma_m * \zeta_m$

$+ \sum_{j=1}^{J} \Phi_j * r_j$

$+ \sum_{j=1}^{J} \kappa_j * \delta_j$

$+ \sum_{j=1}^{J} \tau_j * d_j$

$+ \sum_{j=1}^{J}\sum_{i=1}^{I} (1 - \xi_i) * \chi_j * B_{ji} * d_j$

Subject to

$Q_i^s + \sum_{m=1}^{M}\sum_{c=1}^{C} \lambda_{imc}^{s} = D_i^s$; ∀ (i,s) 1.1

$Z_{imc}^{s} \leq \Upsilon_{im}$; ∀ (i,m,c,s) 1.2

$\lambda_{imc}^{s} \leq M^{\infty} Z_{imc}^{s}$; ∀ (i,m,c,s) 1.3

$\sum_{i=1}^{I} t_{im} \lambda_{imc}^{s} \leq \mu_m N_{mc}$; ∀ (m,c,s) 1.4

$\sum_{m=1}^{M} N_{mc} \leq U_c$; ∀ (c,s) 1.5

$\sum_{m=1}^{M} N_{mc} \geq L_c$; ∀ (c,s) 1.6

$\sum_{c=1}^{C} N_{mc} \leq \zeta_m$; ∀ (c,s) 1.7

$\sum_{i=1}^{I}\sum_{c=1}^{C}\sum_{s=1}^{S} \frac{\lambda_{imc}^{s}}{\mu_m} = \rho_m$; ∀ (m) 1.8

$$\rho_m \leq 1; \forall \text{ (m)} \quad 1.9$$

$$\sum_{m=1}^{M} \sum_{c=1}^{C} \sum_{s=1}^{S} \lambda_{imc}^{s} \leq \xi_i \sum_{j=1}^{J} \mathrm{B_{ji}} * \mathrm{d_j}; \forall \text{ (i)} \quad 1.10$$

$$\mathrm{P}\ (\sigma_{system} \geq \Psi) \leq \Xi \quad 1.11$$

$$r_j \geq d_j; \forall \text{ (j)} \quad 1.12$$

$$d_j \leq M^{\infty}\ \delta_j; \forall \text{ (j)} \quad 1.13$$

$$N_{mc} \leq M^{\infty}\ \alpha_{mc}; \forall \text{ (m,c)} \quad 1.14$$

$$\alpha_{mc} \leq N_{mc}; \forall \text{ (m,c)} \quad 1.15$$

$$\sum_{m=1}^{M} \sum_{s=1}^{S} Z_{imc}^{s} \leq M^{\infty}\ X_{ic}; \forall \text{ (i,c)} \quad 1.16$$

$$\sum_{m=1}^{M} \sum_{s=1}^{S} Z_{imc}^{s} \geq\ X_{ic}; \forall \text{ (i,c)} \quad 1.17$$

$$\lambda_{imc}^{s}\ \ , Q_i^s \geq 0 \ \text{ and integer} \quad 1.18$$

$$N_{mc}, \zeta_m, d_j, r_j, \ \geq 0 \ \text{ and integer} \quad 1.19$$

$$\alpha_{mc}, \delta_j \in \{0, 1\} \quad 1.20$$

Zimcs,
Xic

$$\rho_m \in [0, 1] \quad 1.21$$

Model objective Function: The objective function of the model consists of several cost terms. There are several cost terms pertaining to the second-stage decision variables inside the bracket. Hence, all the other cost terms out of the bracket are related to the first stage decision variables. The first term in the bracket shows the machine operating cost. The second term in the bracket shows the machine breakdown cost. The third term in the bracket shows the outsourcing cost. The fourth term in the bracket is the production cost of the remanufactured parts. The first term out of the bracket addresses the cost of intercellular movements of the parts between cells. The second term out of the bracket demonstrates machine maintenance and overhead costs. The third term outside of the bracket demonstrates machine procurements cost. The fourth term outside of the bracket shows the cost of acquiring returned products. The fifth term outside of the bracket shows the cost of set-up for disassembly operations. The sixth term outside of the bracket is corresponding to the cost of disassembly operations. The last term outside of the bracket is related to the cost of disposing returned products that cannot be economically recovered.

Model Constraints: The objective function of the model is subjected to constraints as follows: Constraint (1.1) demonstrates that the demands for each part type in each scenario can be fulfilled by producing remanufactured products and outsourcing option of the part demands. Noteworthy, the summation of arrival rates of part i on machine m in cell c in scenario s is tantamount to be the production rate of part i in scenario s. Constraint (1.2) ensures that each part is assigned to appropriate machines in each scenario according to the part-machine incidence matrix. Constraint (1.3) indicates that the number of parts produced internally can be positive only if Z_{imc}^{s}= 1, that is, it has been decided that part i would be produced on machine m in cell c in scenario s. Constraint (1.4) ensures that in each scenario the capacity of machines would not be exceeded. Constraint (1.5) demonstrates that the total number of machines in each cell should be equal or less than the upper size limit of the cell. Constraint (1.6) demonstrates that the total number of machines in each cell should be equal or more than the lower size limit of the cell. Constraint (1.7) indicates that the total number of machines in each cell should be less than the number of purchased machines. Through Constraint (1.8), utilization rate of each machine can be calculated. Constraint (1.9) declares that the utilization rates of the machines have to be less than 1. Constraint (1.10) states that the quantity of parts, acquired from returned products, depends on the quality level and bill of the materials (BOM) of the returned products. Constraint (1.11) is a chance-constrained ensuring the probability that the average waiting time of each part in the system exceeding the critical waiting time is less than the service level. Constraint (1.12) shows that the number of acquired returned products should be equal or greater than the number of returned products to be disassembled. Constraint (1.13) indicates a logical constraint for disassembling activities. Constraints (1.14) and (1.15) are for setting α_{mc} to 1 if at least one machine of type m is located in cell c. Constraints (1.16) and (1.17) are for setting X_{ic} to 1 if at least one part of type i is assigned to cell c in scenario s. Set of Constraints (1.18), (1.19), (1.20), and (1.21) specify the logical binary, continuous, and non-negativity integer requirements on the decision variables.

6.2.2 Linearizing the Objective Function

The objective function is a non-linear function due to the non-linear terms of the first cost term outside of the bracket which is related to the intercellular movements of parts. To transform this non-linear term to linear one, the following new variable is defined as follows [44]:

$$\phi_{imc} = \alpha_{mc} * X_{ic} \tag{4}$$

By considering this equation, following constraints must be added to the model [44]:

$$\phi_{imc} \leq X_{ic};\ \forall\ (i,m,c) \qquad 1.22$$

$$\phi_{imc} \leq \alpha_{mc};\ \forall\ (i,m,c) \qquad 1.23$$

$$X_{ic} + \alpha_{mc} - \phi_{imc} \leq 1;\ \forall\ (i,m,c) \qquad 1.24$$

$$\sum_{s=1}^{S} Z_{imc}^{s} = \phi_{imc} \qquad 1.25$$

Also, Constraint 1.11 is a chance-constrained which is equal to $e^{-\mu_j(1-\rho_j)t}$ which can be linearized as follows:

$$-\mu_j (1 - \rho_j)\, t \leq \ln \alpha;\ \forall\ (j) \qquad 1.26$$

After this term is linearized, the objective function of the stochastic mixed integer programming model has linear terms only. All constraints in the mathematical model are linear as well.

6.3 Numerical Example

A number of example problems are solved with the use of CPLEX, a commercially available software. For the clarification purposes, one example problem is explained in detail to show the applications of the proposed model in designing a cellular manufacturing system with remanufacturing option. To clarify the model further, seven extra examples are solved in section 6. In solving the Example, 4 components, 3 machines, 3 cells and 2 scenarios are considered. Also, in the reverse supply chain aspect of the model, there are 3 types of the returned products that need to be collected from the customer zones.

6.3.1 Input data and problem size

The input data of the Example is given in Table 6-1. The input data are generated randomly with respect to the abundant literature review in the fields of cellular manufacturing systems and closed-loop supply chains. Table 6-2 shows the size of the Example. Accordingly, there are 372 constraints as well as 230 integer variables and 3 continuous variables.

Table 6-1 Input data for Example

Parameter	Value
Probability of each scenario s	0.5
Demand for part type i in scenario s	200-700
Procurement cost per machine type m	800
Maintenance and overhead costs per machine type m	1300-1500
Inter-cellular material handling cost per part type i	5
Production cost for each part type i	10
Outsourcing cost for each part type i	150-500
Capacity of one unit of machine type m (Service Rate)	3000
Processing time of part i on machine m	3-6
Operating cost per unit time per machine type m	10
Breakdown cost for machine type m	1200-1800
Upper limit cell size	10
Lower limit cell size	3
Acquiring cost of the returned product j	15-35
Setup cost for disassembling returned product j	20-30
Disassembly cost of returned product j	25-35
Average recovering rate of returned product j	0.9
Number of parts i contained in product j	9-15
Disposal cost of the returned product j	200
Breakdown cost for machine type m	1200-1800

Table 6-1 continued

Parameter	Value
Average time between two consecutive failures of machine type m (hour)	3-8
Average time between two consecutive repairs of machine type m (hour)	50-90

Table 6-2 Generic Attribute of the Example

No. of parts	No. of machines	No. of cells	No. of retuned products	No. of Scenarios	No. of binary variables	No. of integer variables	No. of continuous variables	No. of constraints
4	3	3	3	2	132	98	3	372

6.3.2 Solution of the Example

The solutions of the Example are brought in the Tables 6-3 to-6-7. Table 6-3 demonstrates the arrival rates which are tantamount to be the internal production rates on each and every machine in each cell for each scenario. Table 6-4 shows the number of each part types that needs to be outsourced for a given scenario. Hence, it is necessary to outsource 200 units of part 1 in scenario 2 and 198 units of part 3 in scenario 1 to fulfil the demand without any backorders or lost sales. Table 6-5 shows the number of machine assignments in the cells. Accordingly, 3 machines of type 3 are assigned to cell 1, 3 machines of type 2 are assigned to cell 2, and 3 machines of type 1 are assigned to cell 1. According to Table 6-6, utilization rates of the machines 1, 2, and 3 are 0.6995, 0.7995, and 0.45 respectively. Average number of parts in the queue of each machine is also calculated in Table 6-6. Accordingly, there are approximately on average 2 parts in the queue of machine 1, 4 parts in the queue of the machine 2 and 1 part in the queue of machine 3. Table 6-7 shows the number of returned products that needs to be acquired. Hence, there is a need to acquire 25 returned products of type 1 and 90 returned products of type 2. One extra illustrative example is solved in the Appendix.

Table 6-3 Production rate of the part (I) on the machine (M) in the cell (C) in Scenario (S)

Part (I)	Machine (M)	Cell (C)	Scenario (S)	Value
1	2	2	1	500
2	1	3	1	600
2	2	2	2	600
3	2	2	1	502
3	3	1	2	600
4	1	3	1	700
4	3	1	2	300

Table 6-4 Outsourcing amounts of the part (I) in Scenario (S)

Part (I)	Scenario (S)	Value
1	2	200
3	1	198

Table 6-5 Number of the machine (M) assigned to cell (C)

Machine (M)	Cell (C)	Value
1	3	3
2	2	3
3	1	3

Table 6-6 Utilization rate of the machine (M)

Machine (M)	Utilization	Average Number of parts in the queue
1	0.6495	1.77
2	0.7995	3.987
3	0.45	0.81

Table 6-7 Number of returned product (J)

Returned Product (J)	Value
1	25
2	90
3	0

6.3.3 Value of Stochastic Solutions

In order to highlight the merit of solving the proposed stochastic problem against the expected value problem (the problem in which the stochastic parameters are substituted with their expected values), a common measure is the value of stochastic solution (VSS). Let ($\bar{z}$,$\bar{n}$) denote the optimal solution to the expected value problem (Deterministic Problem). Deterministic equivalent problem is brought in the Appendix. Thus, in our problem, VSS is defined by VSS = ω ($\bar{z}$,$\bar{n}$) - ω *, where ω ($\bar{z}$,$\bar{n}$) is the true objective value of solution ($\bar{z}$,$\bar{n}$) and ω * is the optimum objective value of the true stochastic problem.

Hence, the value of the stochastic solution can be calculated as follows:

$$VSS = \omega\,(\bar{z},\bar{n}) - \omega^{*} = 133{,}153 - 145{,}870 = |-12{,}717| = 12{,}717$$

6.4 Sensitivity Analysis

To investigate the effect of the service level on the objective function value, a sensitivity analysis is done in this section. In addition, to investigate the effects of the quality of the returned products on the objective function value, number of returned products to be acquired, and number of parts to be outsourced, several sensitivity analyses are done. Figure 6-3 demonstrates the effect of service level on the objective function value. In Figures 3 and 4, it is assumed that service level fluctuates between 0 and 1 with the gradual increments of 0.1. According to Figure 6-3, for the service levels from 0 to 0.3, the value of the objective function is 0. It shows that the solution of the mathematical model in the range of 0 to 0.3 is infeasible. Accordingly, the maximum objective function value is for the service level 0.4. Figure 6-3 shows that for the service levels from 0.4 to 0.6, objective function value decreases substantially, and for the service levels between 0.6 to 0.9, objective function value decreases moderately (i.e. lower than the service levels from 0.4 to 0.6).

According to Figure 6-3, the objective function value is roughly the same for the service levels of the 0.9 and 1.0. Figure 6-4 demonstrates that by having higher service levels, the number of parts that needs to be outsourced are decreased. Hence, for the service level 0.4 as the minimum feasible service level, the number of parts that needs to be outsourced has the highest value. According to Figure 6-4, for the service levels from 0.4 to 0.8 with the gradual increment of 0.1, the number of parts that needs to be outsourced are decreased substantially. Figure 6-4 shows that the number of parts that needs to be outsourced are roughly the same for the service levels 0.9 and 1.0.

Figure 6-5 demonstrates the effect of the quality of the retuned products on the objective function value. The minimum acceptable quality level of the returned products is reached by CPLEX to be 0.6. Accordingly, for any value less than 0.6, objective function value remains constant. It is assumed that the quality is the same for all types of the returned products and it fluctuates between 0.6 and 1 with the gradual increment of 0.1. Accordingly, for the quality of 0.6 to 1.0, objective function value starts to decrease significantly.

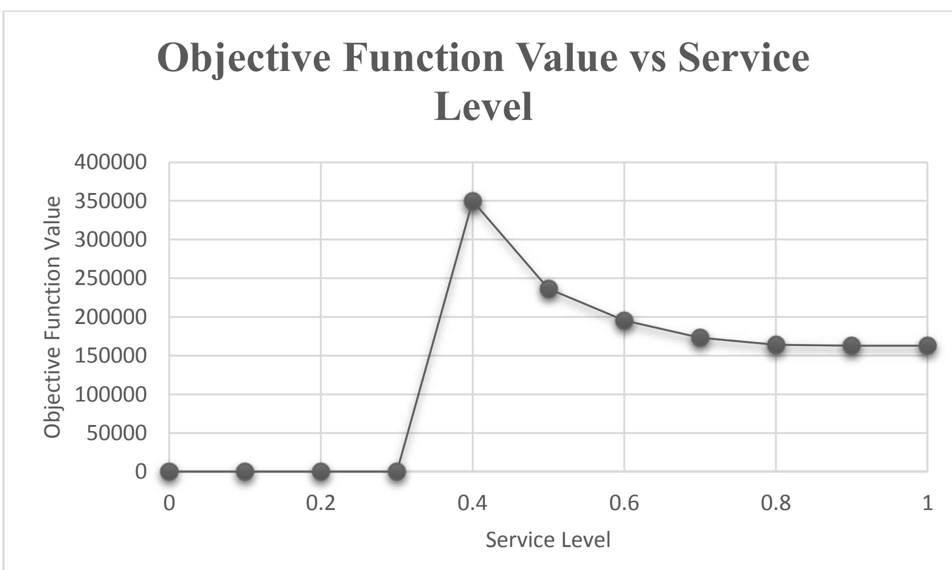

Figure 6-3 *Objective function value versus service level*

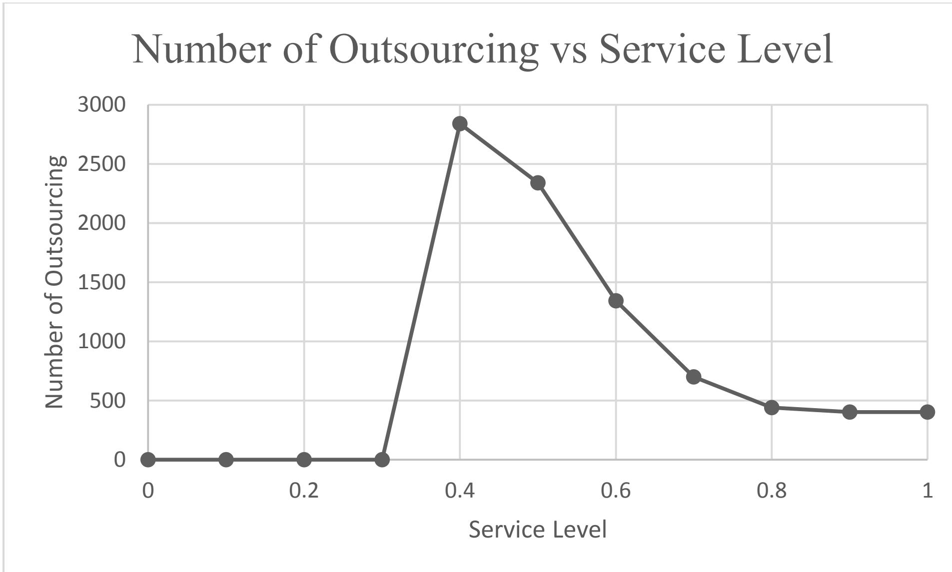

Figure 6-4 *Number of Outsourcing versus service levels*

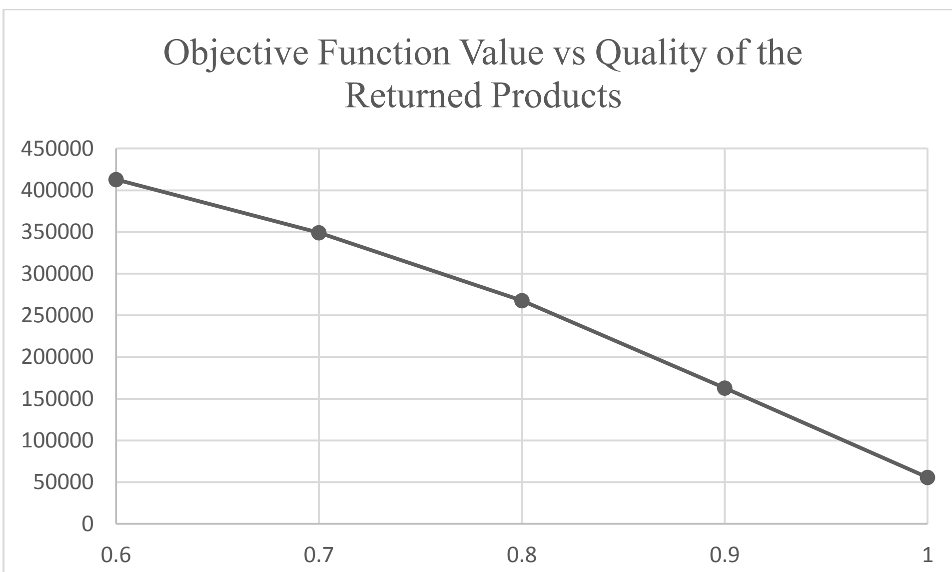

Figure 6-5 *Quality of the returned products versus objective function value*

6.5 Computational Experiments

To further clarify the proposed model, seven extra example problems are solved in this section. According to Table 6-8, all the computational experiments are performed using Intel® Core™2.67 GHz workstation with the problems being solved resorting to IBM ILOG CPLEX Optimization Studio 12.7/OPL. For all the example problems, number of part types, number of machines, number of cells, number of scenarios, and number of returned products are reported. Number of constraints as well as the number of decision variables for each example problem is reported. Seven scenarios are solved for the purpose of calculating value of stochastic solution. A major criterion in solving two-stage stochastic programming is the value of the stochastic solution which demonstrates the potential benefit in solving the stochastic program rather than solving a deterministic program in which expected values are replaced random parameters. According to Table 6-8, scenario problems 1-6 are solved to optimality with the use of CPLEX. However, scenario problem 7 cannot be solved to optimality after approximately 6 hours of computational time with 0.7% optimality gap and the search was stopped due to memory limitations. According to Table 6-8, CPU times have increased as the scenario problems get larger based on the number of decision variables and constraints. According to Table 6-8, value of stochastic solutions are demonstrated for each of the problem scenarios. It can be realized from Table 6-8 that the value of the stochastic solutions (VSS) gets larger as the problem sizes increase.

Table 6-8 Summary of computational results

Problem Scenario	Number of components	Number of scenarios	Number of machines	Number of returned products	Number of cells	Number of variables	Number of Constraints	Solution Time (Seconds)	Objective Function (Two-stage)	Value of Stochastic Solution
1	2	2	2	2	2	66	106	0.74	56,927	9,785
2	2	3	3	2	3	168	269	2.17	122,518	12,262
3	4	3	3	3	3	309	451	2.95	235,928	18,987
4	4	4	4	4	4	660	900	375.61	305,973	19,849
5	5	4	4	4	5	1210	1574	8,071	348,298	23,392
6	5	6	5	5	5	1755	2200	8,650.41	560,406	32,158
7	5	5	5	5	6	2195	2627	21,378*	1,075,974*	-

6.6 Summary of the chapter

We have developed a detailed two–stage stochastic mathematical model on the integration of production planning problem of a cellular manufacturing with the activities in a closed-loop supply chain such as acquisition and disassembly of the returned products and closed-loop supply chain. Reliability concerns of the machines are also considered through the addition of machine breakdown influence in terms of machine overhaul cost and production time loss in calculating the machine operational cost in the model. Mean time between failures (MTBF) and mean time to repairs (MTTR) are two parameters that has been used for the reliability considerations. One the manufacturing aspect of the model in terms of production planning, there are different features such as outsourcing, internal production, capacity and availability and procurements of the machines, and duplications of identical machines in the cells. Acquisition and disassembly of the returned products are considered in the closed-loop supply chain of our mathematical model. To show the applicability of the mathematical model in this paper, one instance is solved and analysed completely. We investigated the effects of the service level on the objective function value and number of parts to be subcontracted as well as the effects of the quality of the returned products on the objective function value. Seven extra instances were also solved to investigate the solution capability of the CPLEX and to calculate the extra advantages that one gains through the use of stochastic programming namely, value of stochastic solutions. Since the mathematical model in this paper is static (i.e. designed for one period), it can further be generalized into a multi-period model. Applying solution technics such as sample average approximations (SAA) and L-Shaped method would be perused for the future research.

Chapter 7 Conclusions and Future Research

7.1 Conclusions

Sustainable manufacturing may be defined as producing products with the use of non-polluting, energy and natural resources conserving, economically sound, and safe processes. Hence, reconfigurable cellular manufacturing systems as a subsection of lean manufacturing, through the use of mass-customization, can be applied in practice to minimize the wastes. Closed-loop supply chains are intrinsically sustainable due to the post-use of modules and materials of the returned products through remanufacturing and recycling in remanufacturing and/or hybrid manufacturing-remanufacturing facilities. Therefore, a sustainable manufacturing system should work as a part of a closed-loop supply chain to form a sustainable network for the whole enterprise. The main objective of this thesis is to design efficient sustainable manufacturing systems to be as a part of a sustainable closed-loop supply chain considering realistic assumptions such as alternative process routings, contingency process routings, lot splitting, reconfigurations, machine adjacency requirements, machine failures, reliability of machines, and quality of the returned products, outsourcing, as well as stochastic and probabilistic parameters.

In Chapter 3, a mixed-integer mathematical model is presented for a third-party remanufacturer in a remanufacturing facility with cellular layout as a part of a closed-loop supply chain. The developed system completely relies on the remanufacturing process. The novelty of this model is primarily about the mathematical model developed with potential applications both at manufacturing/supply chain design and operational stages. The proposed approach involves modeling of a sustainable cellular remanufacturing enterprise that operates as a part of a sustainable closed-loop supply chain. The mathematical model is a novel and a detailed model;

considering a large number of manufacturing attributes such as multi-period production settings, dynamic cell configuration, multi-period production settings, machine capacity, machine acquisition, machine procurement, and multiple units of identical machines as well as considering different cost parameters such as production costs, operational cost of the machines, and subcontracting cost of the part demands. Several activities such as acquisition, disassembly, setup for disassembly, and disposition of the returned products have been considered on the reverse flow of the closed-loop supply chain of the proposed mathematical model. To demonstrate the additional usability of the model at the system design and operational levels, a sensitivity analysis has been conducted to show the effects of quality levels of the returned products on the total costs as well as the total number of acquired returned products. The effects of outsourcing option of the part demands on the objective function value and the total number of acquired returned products have also been investigated.

In Chapter 4, the mathematical model in chapter 3 is extended by taking operation sequences, machine adjacency constraints, alternative process routings, and outsourcing option of the part demands into account. The mathematical model in Chapter 4 proposes an integrated approach towards the design optimization and production planning of cellular manufacturing systems as a part of closed-loop supply chains in an effort to make manufacturing enterprises more sustainable. For industrial applications both at the system design and operation stages, a mixed integer linear programming (MILP) model, to integrate the production planning problem in cellular manufacturing systems and the tactical planning of a closed-loop supply chain, has been developed. The cellular manufacturing system in the proposed mathematical model has several additional features including dynamic cell configuration, multi-period production settings, machine capacity, machine acquisition, machine procurements, and multiple units of identical machines as well as considering different cost parameters such as production costs, operational cost of the machines, and subcontracting cost of the part demands. In addition, several activities such as acquisition, disassembly, setup for disassembly, and disposition of the returned products have been considered on the reverse flow of the closed-loop supply chain of the proposed mathematical model. To further demonstrate the application of the proposed mathematical model in practice, several sensitivity analyses have been done to show the effect of quality of the returned products, alternative process routings, and outsourcing option of the part demands on the objective function value and the number of acquired returned products.

To incorporate the application of hybrid manufacturing-remanufacturing systems in designing sustainable manufacturing systems and to extend the previous mathematical models in Chapter 3 and Chapter 4, a detailed mathematical model is developed in Chapter 5. Hence, the mathematical model in Chapter 5 is developed for an original equipment manufacturer in a hybrid manufacturing-remanufacturing facility with cellular layout to work as a part of a closed-loop supply chain. The mathematical model in Chapter 5 integrates the production planning problem of hybrid cellular manufacturing-remanufacturing systems with the tactical planning of closed-loop supply chains to design a sustainable enterprise. The proposed mathematical model is a detailed one which encompasses various features in manufacturing and closed-loop supply chain aspects. The model features dynamic cell configuration, multi-period production setting, alternative process routings, contingency process routings, and reliability of machines, machine capacity, machine acquisition, machine procurements, and multiple units of identical machines, quality of the returned products, and the number of returned products to be acquired, disassembled, and kept in the inventory. The proposed model also considers various cost elements such as production costs, operational cost of the machines, reconfiguration cost, and inventory holding cost as well as costs related to the closed-loop supply chain such as acquisition, inventory holding, and disassembly of the returned products. The proposed mathematical model has been solved for different instances to investigate the solution capability of CPLEX and to show the effect of alternative process routings and contingency process routings on the objective function value.

In designing sustainable manufacturing systems as a part of a sustainable closed-loop supply chain, there cannot be found any research article in the literature on the application of stochastic programming and/or queuing theory. To extend the mathematical model in Chapter 3, a mixed-integer mathematical model, in Chapter 6, is developed for a third party remanufacturer in a remanufacturing facility with cellular layout to work as a part of a closed-loop supply chain. The mathematical model in Chapter 6 is a detailed model with the use of realistic assumptions including reliability of machines, probabilistic parameters such as mean time between two consecutive failures and mean time to repair of the machines, as well as stochastic parameters such as demand and outsourcing cost. A queuing-based approach is considered for the model in a Jackson queuing network wherein the production quantity in each cell on each machine type is tantamount to be the arrivals and the capacity of each machine is tantamount to be the service rate of the queue behind of each machine. To avoid a long waiting time of the parts in the queuing system, a chance-constrained is added to the mathematical model as well. The proposed model is considered to be static (single-period) to efficiently apply two-stage stochastic programming. The proposed mathematical model encompasses various cost elements in both of the manufacturing and closed-loop supply chain aspects such as production cost, maintenance and overhead costs of the machines, machine operational cost, machine breakdown cost, material handling cost, and the costs related to acquisition and disassembly of the returned products. The proposed model has been solved for different instances to investigate the solution capability of CPLEX and to calculate the value of stochastic solution.

The mathematical models in this dissertation are mainly targeted to be used in industry at the operational level which would lead to further industrial applications mainly at the integrated design stage of manufacturing and supply chain systems in addition to the potential applications at the operational level. The likely users of the models are the designers of sustainable manufacturing/supply chain systems at the design stage as well as the managers running such systems at the operational level. All the models in this dissertation have been formulated, solved, analyzed, together with this, sensitivity analyses for representing the usability of the models in practice have been presented.

7.2 Future Research

The future work for this dissertation can be summarized as follows:

1- All the proposed mathematical models in this dissertation have been solved with the use of CPLEX. Hence, developing efficient solution approaches, especially exact solution algorithms such as Benders-decomposition and L-shaped method are recommended.

2- The mathematical model in Chapter 6 is developed with the use of two-stage stochastic programming approach for a single period. Therefore, the mathematical model can be generalized to a multi-period version with the aim of multi-stage stochastic programming.

3- Workforce management is one of the most important aspects in designing cellular manufacturing systems, so the incorporation of workers will be perused for the future versions of the mathematical models in this dissertation.

4- For the hybrid manufacturing-remanufacturing system in Chapter 5, additional recovery options such as recycling, reuse 'as is', repair, and refurbishment can be considered.

5- Robust counterparts of the mathematical models in this dissertation will be considered as one of the directions for the future studies.

6- In order to examine the capability of the mathematical models in this dissertation in real-life problems, applying these models on a real case study will be considered.

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Appendix

Extra example for the mathematical model in Chapter 6:

I	S	Demand
1	1	1500
1	2	1200
2	1	1600
2	2	1600
3	1	1700
3	2	1600
4	1	2700
4	2	3300

Production Routing

I	M	C	S
1	1	1	1
1	2	1	1
1	1	3	2
1	2	3	2
1	3	3	2
2	1	3	1
2	2	3	2
2	3	3	2
3	1	3	2
3	2	3	1
3	3	3	1
4	1	1	2
2	2	1	2
4	2	3	1

Machine	Utilization
M1	0.96667
M2	0.96667
M3	0.6