Journal of Industrial and Systems Engineering
Vol. 13, No. 4, pp. 98-123
Autumn (November) 2021

A mathematical model for designing sustainable cellular remanufacturing systems

Amirreza Hooshyar Telegraphi[1*], Akif Asil Bulgak[1]

[1]*Department of Mechanical, Industrial, and Aerospace Engineering, Gina Cody School of Engineering and Computer Science, Concordia University, Montreal Quebec Canada, H3G 1M8*

amirrezatelegraph@gmail.com, bulgak@encs.concordia.ca

Abstract

This article 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 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 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 cost, operational cost of the machines, and subcontracting cost of the part demands; mainly targeted to be used in industry at the operational level. 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, 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.

Keywords: Sustainability, sustainable manufacturing, cellular manufacturing systems, remanufacturing, mathematical programming

1- Introduction

Developing mathematical models for the design of reconfigurable dynamic cellular manufacturing systems into tactical planning of the closed-loop supply chains management is in its infancy era. On the other hand, while sustainability has been a popular research area in closed-loop supply chains and reverse logistics, there has not been much emphasis on the design problems for sustainable manufacturing systems. Sustainability is one of the major issues for companies to be successful in today's business world. In general, sustainability brings different meanings into minds such as green, clean, maintain, retainment, stability, ecological balance, natural resources and environment (Badiru , 2010). According to Kishawy et al. (2018), there is no universal definition for the term sustainability. Sustainability may be defined as "meeting the needs of the present without compromising the ability of future generations to meet their own needs".

*Corresponding author
ISSN: 1735-8272,

In manufacturing systems, sustainability may be defined as producing products that use processes having less negative environmental impacts, safe for employees, and economically sound (Jayal et al., 2010). 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 (Garbie , 2013). 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 along with the forward flows and the second one refers to the pillars of sustainability in supply chain design that is economical, ecological, and social aspects of an organization (Boukherroub et al., 2017). While sustainability has been a popular research area in closed-loop supply chain and reverse logistics, there has not been much emphasis on the design problems for sustainable manufacturing systems. For sustainable manufacturing systems, resorting to cellular manufacturing systems and reconfigurable manufacturing systems are highly recommended (Garbie, 2013). 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. "Group Technology is a technique for identifying and bringing together related or similar components in order to take advantage of their similarities in the design and manufacturing process". By grouping similar parts together, manufacturing cells can be created. This is based on the similar operations of the parts with respect to their similarities in production and design. Required machines are then physically assigned to producing part families (Balakrishnan and Cheng, 2007). In conventional cellular manufacturing systems, the main assumption was to keep the product mix and part demands 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 in manufacturing facilities; for instance, reduction in parts movements, set-up time, waiting time between operations, and work-in-process inventory. 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 (www.rlmagazine.com). 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 (Wang et al., 2011). Manufacturers worldwide concentrate on remanufacturing option owing to the fact that remanufacturing conserve the value-added to the components during remanufacturing processes. There are many benefits for companies implementing remanufacturing operations including savings in labor, materials and energy costs, shorter production lead times, balanced production lines, new market development opportunities, and a positive socially concerned image for firms (Baki et al., 2014). According to Kishawy et al. (2018) in order to design for sustainable manufacturing systems, several plans need to be considered including: Plan for repair, reuse, and recycle; Plan for reducing hazardous materials and wastes; Plan for disassembly of the products; Plan for taking continuous improvements into account; Plan for energy efficiency; Plan for remanufacturing the returned products; Plan for optimal usage of the materials; Plan for cost efficacy.

The mathematical model proposed in this paper encompasses the first, second, third, fourth, sixth, and eight of the plans mentioned in Kishawy et al. (2018). The remainder of this paper is organized as follows: Section 2 reviews the relevant literature to the mathematical model proposed. Detailed description of the mathematical model and its linearization are presented in section 3. A detailed discussion of a numerical example of the proposed model is given in section 4. In section 5, conclusions and future research are presented.

2- Literature review

2-1- Reconfigurable cellular manufacturing system design

Shorter life cycles of the products, higher varieties of different products, probabilistic demands, and shorter delivery times encourage researchers to investigate on designing manufacturing systems which can decrease the uncertainties contained in production planning quickly (Guo and Ya, 2015). Hence, cellular manufacturing systems have received an increasing attention in the recent years. Literature reviews pertinent to the mathematical models and solution approaches in designing cellular manufacturing systems with reconfiguration are reviewed.

Landers et al. (2001) were the first authors who introduced the concept of "reconfigurability" for a manufacturing system. Principal features, advantages, and a classification of reconfigurable manufacturing systems (RMSs) were presented by Koren and Shpitalni (2010). They also proposed a mathematical model for designing the RMSs. Eguia et al. (2013) proposed a mixed integer linear programming model to solve the cell formation problem and the production scheduling of the part families for a reconfigurable cellular manufacturing system (RCMS). They used the off-the-shelf optimization software CPLEX to show the applicability of the proposed mathematical model for small instances. They developed a tabu search (TS) algorithm for solving large-sized instances of the model. Results demonstrated that TS requires shorter computational times to give near-to-optimal solutions with less than 10% deviations from the optimal solutions overall.

Purchek (1975) was one of the first authors who introduced a linear programming (LP) model to formulate part/machine groups. Purchek's (1975) p-median model is the first model to cluster n parts (machines) into p part families (machine cells) using mathematical programming. Chen and Cao (2004) presented a nonlinear mixed integer programming model to investigate the application of production planning problem in cellular manufacturing system. Their model aimed at minimizing costs related to inter-cell material handling, manufacturing setup, cell setup, inventory holding and production planning. These authors developed a TS algorithm to solve the model. Tavakkoli-Moghaddam et al. (2005) 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. (2005, October) proposed a multi-objective dynamic cell formation problem including several important features of cellular design such as alternative process plan, sequence of operations, and machine relocations. The objective function of their model determined the optimal number of cells, optimal amounts of machine relocation cost and optimal inter-cell movements cost in different time periods. They used the combination of memetic algorithm (MA) and SA approach for solving their model. Defersha and Chen (2006) proposed a nonlinear mixed-integer mathematical model for designing a cellular manufacturing system. Their model incorporated dynamic cell configuration, alternative routings, lot splitting, sequence of operations, multiple units of identical machines, machine capacity, workload balancing among 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. Defersha and Chen (2008) 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 genetic algorithm. Deferesha and Chen (2008) developed a parallel genetic algorithm approach to solve cell formation problem in a dynamic environment. Computational results demonstrated the efficiency of the proposed approach over sequential genetic algorithm and off-the-shelf optimization software. Tavakkoli-Moghaddam et al. (2008) developed a multi-period mixed integer mathematical model to minimize the inter-cell movement and machine relocation costs simultaneously. Due to the NP-hardness of the problem, which cannot be solved in polynomial time, a SA algorithm was developed to solve the model. Results obtained demonstrated that there is less than 4 percent gap in the optimal and near optimal solutions. Bulgak and Bektas (2009) extended Defersha and Chen's (2006) model by proposing a nonlinear mixed integer mathematical model by addressing formation of compact cells by introducing intra-cellular movement of parts. Some linearization techniques were followed to solve their mixed integer model. Their model was solved using off-the-shelf software CPLEX. Ah kioon et al. (2009) proposed a nonlinear mixed integer mathematical model for designing a cellular manufacturing system by considering multi-period production planning, dynamic system reconfiguration, operation sequences, duplicate machines, machine capacity, machine procurement, lot splitting and contingency process routings. Duplicate machines refer to the identical machines that are used in the cells. They added contingency process routings to the model to prevent cellular manufacturing system work intermittently due to machine breakdowns or workload imbalances. They solved the model using CPLEX. Jayakumar and Raju (2010) developed a multi-period, non-linear mathematical cell formation model and solved it with LINGO commercial software for small and medium sized problems. For small-sized problems the problem could be solved optimally while for medium size problems solving the problem in a reasonably fleeting period of time was not possible. The model encompassed several real-life parameters like alternate routing, operation sequence, duplicate machines, product mix, product demand, batch size, processing time, and machine capacity. Mahdavi et al. (2010) developed an integer mathematical model for designing a cellular manufacturing system considering worker assignments. Their mathematical model aimed at minimizing holding and backorder costs, inter-cell material handling cost, machine and reconfiguration costs and hiring, firing and salary costs. They considered several manufacturing attributes such as multi-period production settings, dynamic system reconfiguration, duplicate machines, machine capacity, available time of workers, as well as worker assignments. They used off-the-shelf optimization software LINGO for solving their proposed mathematical model. Sharifi et al. (2012) developed a mathematical model for designing a dynamic cellular manufacturing system. Their model aimed at minimizing setup time in the sequence-dependent manufacturing cells. They improvised a genetic algorithm approach for solving the mathematical model. Niakan et al. (2016) developed a bi-objective model featuring skill-based assignment of the workers. The first objective of the model was to minimize the costs of production and labors while the second objective was to minimize $\mathrm{CO_2}$ emissions, raw materials and energy consumption. They solved the model using non-dominated sorted genetic algorithm II (NSGA II) to reach to near-to-optimal solutions. Aljuneidi and Bulgak (2016) presented a mathematical model for designing a cellular remanufacturing system considering worker assignments. They considered several manufacturing attributes in their model such as multi period production planning, dynamic system reconfiguration, duplicate machines, machine capacity, and machine procurement. Their model was solved using CPLEX. Soolaki et al. (2018) designed a detailed mathematical model for integrating operational decisions of a cellular manufacturing system and strategic design of a supply-chain. In their model, several decision variables were related to the supply chain including the location of production facilities, procurement of raw materials, shipment of raw materials to the production facilities, as well as distribution of products to the markets. To find near-to-optimal solutions, they applied genetic algorithm. Aalaei and Davoudpour (2017) developed a robust mathematical model for designing a cellular manufacturing system working as a part of closed-loop supply chain. Decisions on the closed-loop supply chain part of the model were strategic. They solved the model with use of CPLEX. Raoofpanah et al. (2019) developed a mathematical model for designing a cellular manufacturing enterprise. Their model aimed at minimizing environmental hazards caused by transportation vehicles. They solved the model to optimality with the use of Benders-decomposition. Eglimez et al. (2017) developed a non-linear stochastic mathematical model for designing a dynamic cellular manufacturing system. They developed a novel solution approach, namely stochastic genetic algorithm in solving the cell formation problem. Their proposed solution approach reduced the solution time significantly. Mahootchi et al. (2018) developed a two-stage stochastic model for designing a cellular manufacturing system considering process routings and outsourcing of the part demands. They solved the model with the use of GAMS software for the small instances. They utilized sample average approximation (SAA) method for to reduce the solution times for the larger instances of the mathematical model. Golmohammadi et al. (2018) designed a stochastic cellular manufacturing system considering stochastic part demands. They solved the model to optimality with a commercial optimization software GAMS. They applied GA for large-sized instances of the mathematical model. Forghani and Fatemi Ghomi

(2019) developed a mathematical model for designing a cellular manufacturing considering queuing theory and process routings of the parts. They applied a heuristic method to get near-to-optimal solutions.

2-2- Remanufacturing system design

Along with legal trends in designing closed-loop supply chains on the rise of concerns associated with environmental issues such as carbon emissions and solid waste generation, the increasing pressures from non-governmental organizations to be more environmentally friendly eventuated in strict attentiveness towards designing sustainable manufacturing enterprises (Jeihoonian et al., 2017). Closed-loop supply chains may also increase the revenue of companies by extending the life cycle of the products through different recovery options such as recycling, refurbishing, remanufacturing, and repairing. Remanufacturing as one of the recovery options refers to processes in which the returned merchandises are transformed into like-new ones such that the quality state and other standards usually will be the same with the new products. In this section, a literature review has been done on remanufacturing system design as one of the significant activities contained in the reverse flow of different products to the original equipment manufacturers. Demirel and Gökçen (2008) developed a mixed integer mathematical model for designing a remanufacturing system including both forward and reverse flows in the closed-loop supply chain. Their model encompassed taking different operational and strategic decisions including optimal production quantities and transportation of manufactured and remanufactured products along with the optimal locations of disassembly, collection and distribution facilities. They solved the model using GAMS software. Mutha and Pokharel (2009) developed a multi-echelon mixed integer mathematical model for designing a reverse logistic network. They assumed that a portion of capacities in different facilities are assigned for remanufacturing activities. They solved the model using GAMS software. Results obtained demonstrated that transportation and other logistic costs may not have prominent effect on the network design. Rather reprocessing and remanufacturing costs as well as the purchasing costs of the new modules can be the very important factor for designing a reverse logistic network. Accordingly, it would be profitable for the firms to locate their reprocessing centers in the regions that new modules and resources such as labor, land, and energy can be obtained at lower prices. Doh and Lee (2010) proposed a mixed integer model for production planning of a remanufacturing system aims at maximizing total profits. Their model contains encompasses decisions about 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 in a multi-period setting. They solved the model using CPLEX. Wang et al. (2011) developed a liner programming model for production planning of a hybrid manufacturing- remanufacturing system with deterministic returns. Hasanov et al. (2012) 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. (2013) presented a Markov decision process model to investigate the effect of integrating disposal decisions in a hybrid manufacturing-remanufacturing system. They solved the model using a heuristic approach. Baki et al. (2014) 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.

Chen and Abrishami (2014) presented a mixed integer mathematical model aim at minimizing the total costs of a hybrid manufacturing-remanufacturing system. Their mathematical model integrates operational decisions of a manufacturing system and tactical decisions of a closed-loop supply chain. 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 decomposition to efficiently solve the mathematical model in reasonable amounts of computational time. Guo and Ya (2015) presented a stochastic model to optimally determine manufacturing and remanufacturing lot sizes considering minimum quality level of returned products. The quality of returns was assumed to have exponential distribution. Results obtained revealed that when the quality of the returned products is low, average total cost remains low, but remanufacturing cost is high. They solved the model with LINGO for small instances of the model. They applied Particle Swarm Optimization (PSO) and GA for solving large instances of the mathematical model. Aljuneidi and Bulgak (2015) developed a nonlinear mixed integer programming model for designing a cellular manufacturing system considering workforce management and remanufacturing the returned products. Several important features of the cellular manufacturing such as inter-cell movements, intra-cell movements, machine procurement, and machine capacity were incorporated in the model. They solved their model using CPLEX software for small-to-medium sized problems. Aljuneidi and Bulgak (2016) investigated the combination of reconfigurable cellular manufacturing systems with hybrid manufacturing remanufacturing systems as an effort to design sustainable manufacturing systems. Their model encompassed the integration of tactical decisions pertaining to the closed-loop supply chain and operational decisions of the cellular manufacturing system in designing sustainable manufacturing systems. They developed a mixed integer mathematical model integrating a classical cell formation problem with reconfiguration, and production planning problem in a hybrid manufacturing remanufacturing environment. The overall objective function of the model was to minimize the total costs including machine costs, manufacturing and remanufacturing costs, and costs related to returned products. They used CPLEX for solving the model. Jeihoonian et al. (2017) developed a two-stage stochastic mathematical model for designing a closed-loop supply chain entailing several types of recovery options such as recycling and remanufacturing. They considered the uncertainty in the quality status of the returned products as a binary variable namely functional and non-functional states. They applied a scenario reduction scheme based on a modified Euclidean distance measure to include most pertinent scenarios only. They solved the mathematical model using L-shaped method. Fang et al. (2017) developed a mixed integer model to minimize the total configuration costs of the system considering stochastic demands for both manufactured and remanufactured products. They assumed both manufacturing and remanufacturing use the same resources. They solved the model to optimality using the Lagrangian-relaxation approach. Liu et al. (2019) developed a mathematical model for designing a hybrid manufacturing-remanufacturing system considering resource depletion and environmental deterioration. They solved the model to minimize the total configuration cost of the manufacturing system using 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 decreases dramatically 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 huge effect on increasing the total cost and the running time of their proposed solution methodology. In another research paper, Aljuneidi and Bulgak (2020) developed a mathematical model for designing a sustainable hybrid manufacturing-remanufacturing system considering carbon emissions. They solved the model using CPLEX software.

From our review, we found that designing sustainable manufacturing enterprises has received increasing attention in recent years. One of the recommended manufacturing systems to achieve sustainability in manufacturing system is cellular manufacturing system. In designing sustainable manufacturing systems, remanufacturing as one of the most important recovery options should also be considered because of its social, economic, and environmental benefits. Tables 1 and 2 show the summary of the literature review pertaining to the design of reconfigurable cellular manufacturing system and remanufacturing system.

Table 1. Details of research on reconfigurable cellular manufacturing system design

Author	Year	Solution Method	Inventory	Lot Splitting	Worker Element	Material Handling	Alternative Routings	Objective Function
Purchek	1975	Heuristic	✓					Configuration Cost
Chen and Cao	2004	TS				Inter-cell		Configuration Cost
Tavakkoli-Moghaddam et al.	2005	GA, TS, SA				Inter-cell		Configuration Cost
Tavakkoli-Moghaddam et al.	2005	MA, SA				Inter-cell		Configuration Cost
Defersha and Chen	2006	Exact (LINGO)	✓	✓		Inter-cell	✓	Configuration Cost
Defersha and Chen	2008	GA	✓	✓		Inter-cell	✓	Configuration Cost
Defersha and Chen	2008	GA	✓	✓		Inter-cell	✓	Configuration Cost
Tavakkoli-Moghaddam et al.	2008	SA				Inter-cell	✓	Configuration Cost
Ahkioon et al.	2009	Exact (CPLEX)	✓	✓		Inter-cell	✓	Configuration Cost
Ahkioon et al.	2009	Exact (CPLEX)	✓	✓		Inter-cell Intera-cell	✓	Configuration Cost
Jayakumar and Raju	2010	Exact (LINGO)				Inter-cell	✓	Configuration Cost
Mahdavi et al.	2010	Exact (LINGO)	✓		✓	Inter-cell		Configuration & Worker Cost
Sharifi et al.	2012	GA				Inter-cell	✓	Configuration Cost
Niakan et al.	2016	NSGA (II)			✓	Inter-cell Intra-cell	✓	Configuration Cost
Aljuneidi and Bulgak	2016	Exact (CPLEX)	✓		✓	Inter-cell		Configuration & Worker Cost
Soolaki et al.	2017	HGALO		✓		Inter-cell	✓	Configuration Cost
Aalaei and Davoudpour	2017	Exact (CPLEX)	✓		✓	Inter-cell		Configuration & Worker Cost
Eglimez et al.	2017	Stochastic GA			✓	Inter-cell		Configuration & Worker Cost
Raoofpanah	2018	Exact (Benders-decomposition)	✓	✓		Inter-cell Intra-cell	✓	Configuration Cost
Mahootchi	2018	Exact (GAMS), SAA	✓	✓		Inter-cell Intra-cell	✓	Configuration Cost
Golmohammadi	2018	Exact (GAMS), GA				Inter-cell Intra-cell		Configuration Cost
Forghani and Fatemi-Ghomi	2018	Heuristic	✓	✓		Inter-cell Intra-cell	✓	Configuration Cost

Table 2. Details of research on remanufacturing system design

Author	Year	Main Work	Solution Approach
Demirel and Gökçen	2008	Optimal production quantities and optimal decisions regarding the transportation of manufactured and remanufactured products along with the optimal locations of disassembly, collection and distribution facilities.	Exact (GMAS)
Mutha and Pokharel	2009	Designing a reverse logistic network. Optimal decisions on several strategic and operational activities in a closed-loop supply chain network.	Exact (GAMS)
Doh and Lee	2010	Designing a remanufacturing system aims at maximizing total profits.	Exact (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
Baki et al.	2014	Finding the optimal lot sizes of manufactured and remanufactured products.	
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
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.	Exact (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.	Exact (CPLEX)
Jeihoonian et al.	2017	Designing a closed-loop supply chain. Optimal decisions on various strategic and tactical activities pirating to a closed-loop supply chain system.	L-shaped
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.	Exact (CPLEX)

3- The mathematical model

3-1- Problem description and formulations

In this paper, design optimization of a cellular manufacturing system as a part of a closed-loop supply chain has been investigated to form a sustainable manufacturing enterprise. According to figure 1, this closed-loop supply chain includes both forward and reverse networks of the remanufacturing facility. In the forward chain, returned products are remanufactured to fulfil the demands of customers. On the other hand, in 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 a number of activities such as disassembly, cleaning, repairing, reassembly and refurbishing. Recognizing the suitable manufacturing layouts can highly increase the efficiency of remanufacturing processes which leads to a design of a sustainable manufacturing system. To achieve sustainability in manufacturing systems, cellular manufacturing layouts are highly recommended. The proposed model considers several manufacturing attributes such as multi-period production settings, reconfigurable layouts of the system, machine duplication which refers to multiple units of identical machines, machine acquisition and machine capacity. There are several parameters pertaining to 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 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 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. 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.

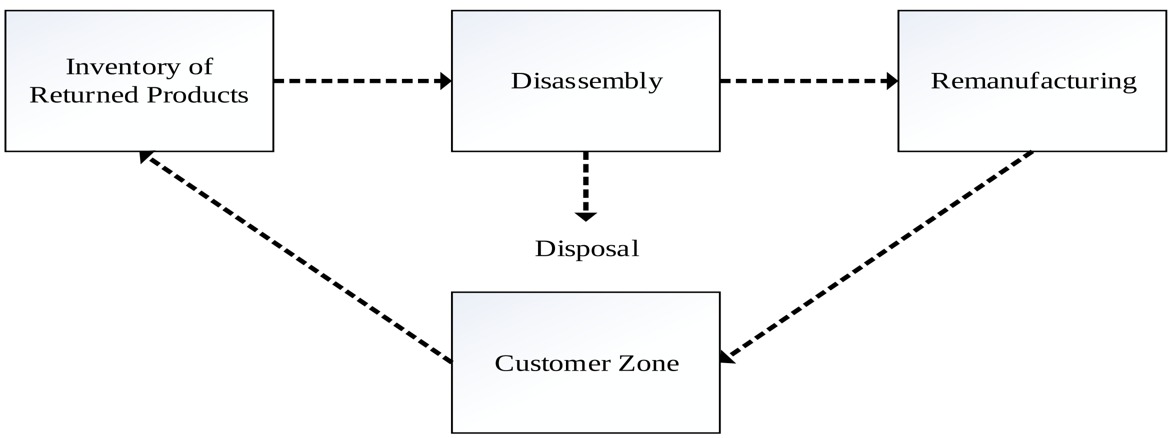

Fig 1. Material flow diagram for the proposed cellular remanufacturing system

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 cells and relocation from one cell to another in different time periods at the beginning of each time period.
- The machine maintenance and overhead costs are known and constant in each time period. These costs are considered for each machine in each cell and period regardless that the machine is active or idle.
- The demand for each component 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.
- Supply of the returned products are deterministic and known in advance.

3-3- 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 = {1, 2, 3 … I}	Index set of part types
m = {1, 2, 3 … M}	Index set of machine types
c = {1, 2, 3 … C}	Index set of cells
t = {1, 2, 3 … T}	Index set of time periods
j = {1, 2, 3 … 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 parts 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

3-4- Model formulation and description

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Objective function

Minimize

Subject to:

$$Q_{it-1} + X_{it} - Q_{it} = D_{it};\ \forall\ (i, t) \tag{2}$$

$$\tau_{ict} = \min\left(1, \sum_{m=1}^{M} Z_{imct}\right);\ \forall\ (i, c, t) \tag{3}$$

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

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

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

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

$$\sum_{i=1}^{I} Z_{imct}\, \rho_{im}\, X_{it} \leq N_{mct}\ \pi_{mt};\ \forall\ (m, c, t) \tag{8}$$

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

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

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

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

$$f_{jt} + d_{jt} - f_{jt-1} = r_{jt};\ \forall\ (j, t) \tag{13}$$

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

$$X_{it} \leq U_i \sum_{j=1}^{J} V_{ij}\, d_{jt};\ \forall\ (i, t) \tag{15}$$

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

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

$$Q_{it}, X_{it} \geq 0;\ \forall\ (i, t) \tag{18}$$

$$\zeta_{mt}, \widehat{A}_{mt} \geq 0;\ \forall\ (m, t) \tag{19}$$

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

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

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.

Constraints: The objective function of the model is subjected to constraints as follows: equation (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. Equation (3) is pertinent to intercellular movements of the parts stating that if part type i is processed in cell c in each time period. Equation (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. Equation (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 equations (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. Equation (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. Equation (12) declares that total number of machines in each cell should not exceed the total number of available machines. Equation (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.

3-5- 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 Coelho (www.leandro-coelho.com) 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:

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

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

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

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

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

$W_{imct} \leq X_{it}$; ∀ (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:

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

$\sum_{m=1}^{M} Z_{imct} \geq \tau_{ict}$; ∀ (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 and 4, respectively, based on the indices of the variables in the proposed model.

Table 3. 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	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 4. Number of constraints in the linearized model

-	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)			

4- 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 12.6/OPL a commercially available optimization software. The data set used is based on the data used by Mahdavi et al. (2010) and Chen and Abrishami (2014). 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 12.6/OPL. Table 5 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 5. Accordingly, CPLEX is not able to solve the last test problem namely problem scenario 7 which is a large-scale instance after 14422 seconds with 0.06% optimality gap. After running the optimization software for 14422 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 5 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 5. 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

4-1- 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 6-10. Table 6 contains costs pertaining to different machine types as well as the capacity of each machine. Table 6 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 7 demonstrates costs related to returned products including disassembly, acquisition, inventory holding, and setup for disassembly. Table 8 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 8, outsourcing cost has been generated randomly in the range of (250, 1000). Table 9 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 10. For example, there are 8 parts of type 4 contained in returned product 3.

Table 6. Data related to different machine types

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 7. 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 8. Data related to different part types

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 9. 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 10. 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

4-1-1- Solution of example 1

Production route of each part type in terms of machines and cells in each period is given in table 11. Table 11 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. 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 12. 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 4-1-2.

Table 11. 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

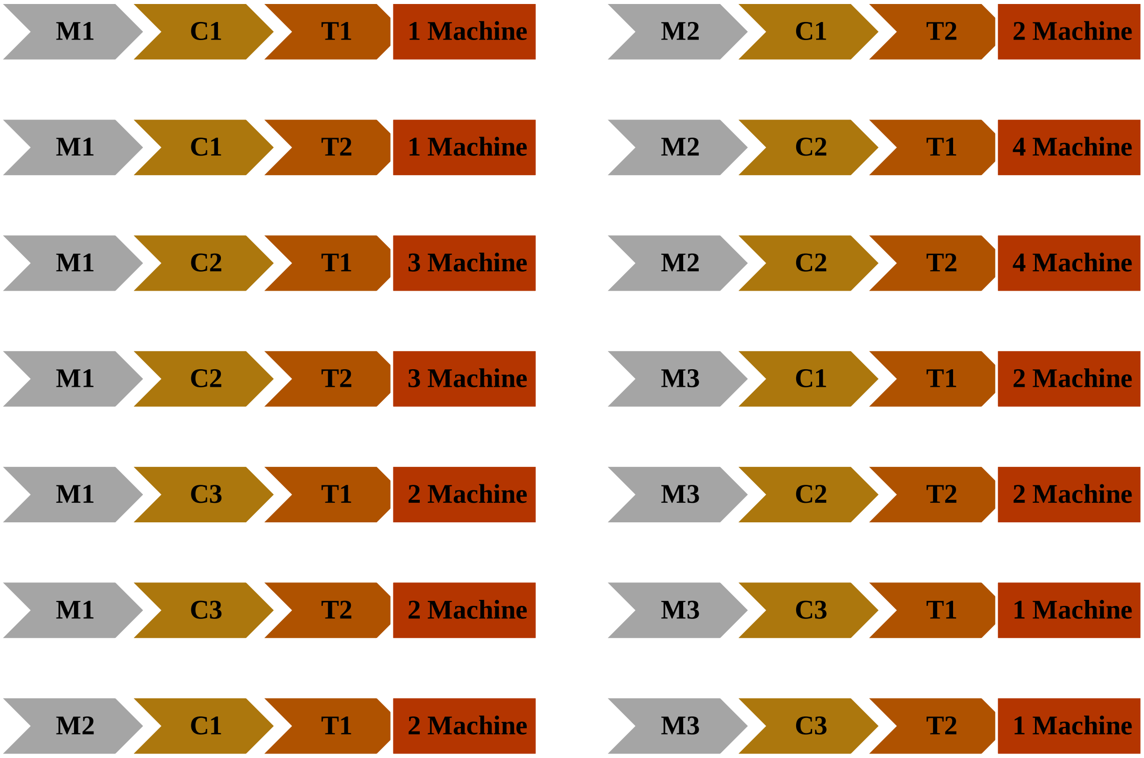

Fig 3. Allocation and quantity of machine types

Table 12. 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

4-1-2- 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 4 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 4, 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 5 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 5 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 6 demonstrates the effects outsourcing option on the number of acquired returned products. According to figure 6, number of acquired returned products decreased from 791 to 419 while taking outsourcing option into account in satisfying the part demands. Figure 7 also demonstrates the effect of outsourcing option on the total costs in the objective function. According to figure 7, 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.

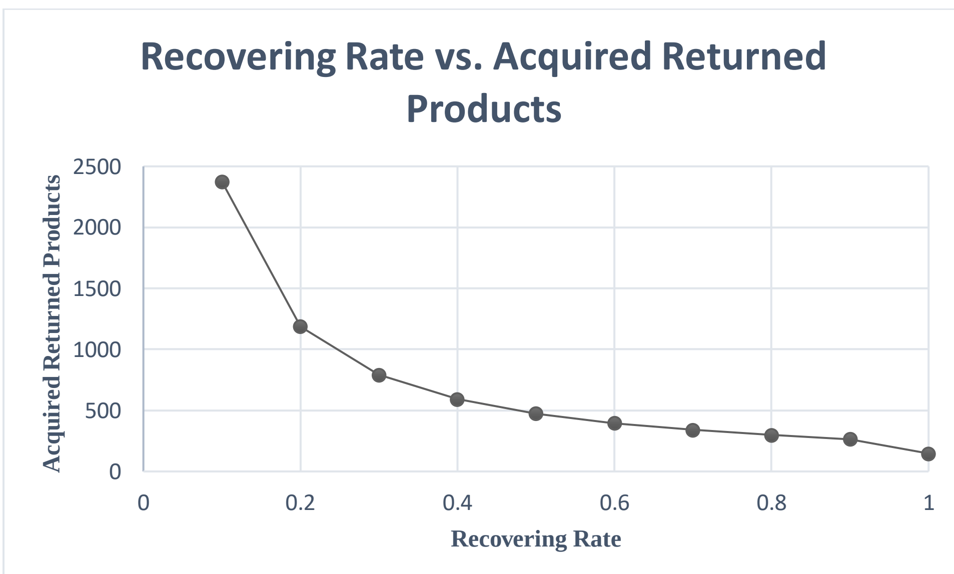

Fig 4. Total cost versus recovery rate

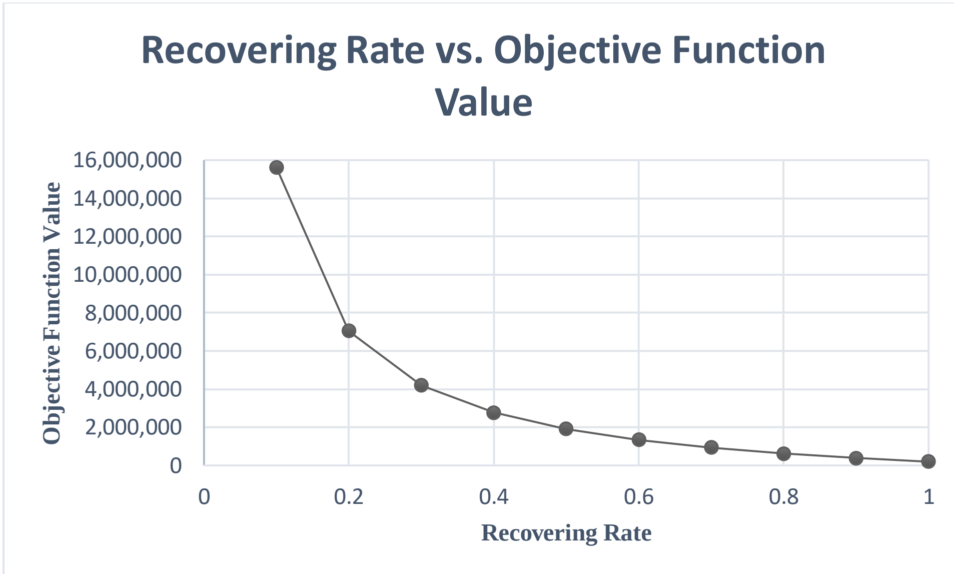

Fig 5. Acquired returned products versus recovery rates

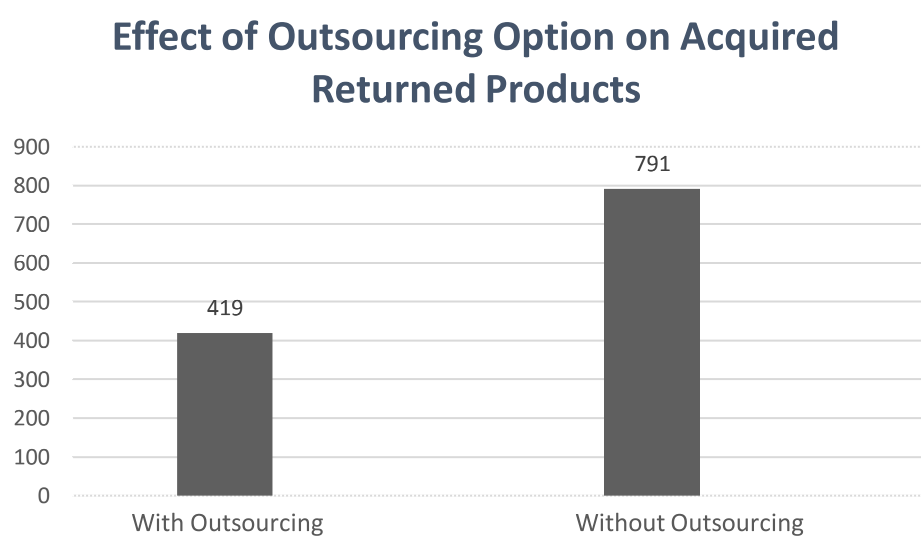

Fig 6. Effect of outsourcing option versus acquired returned products

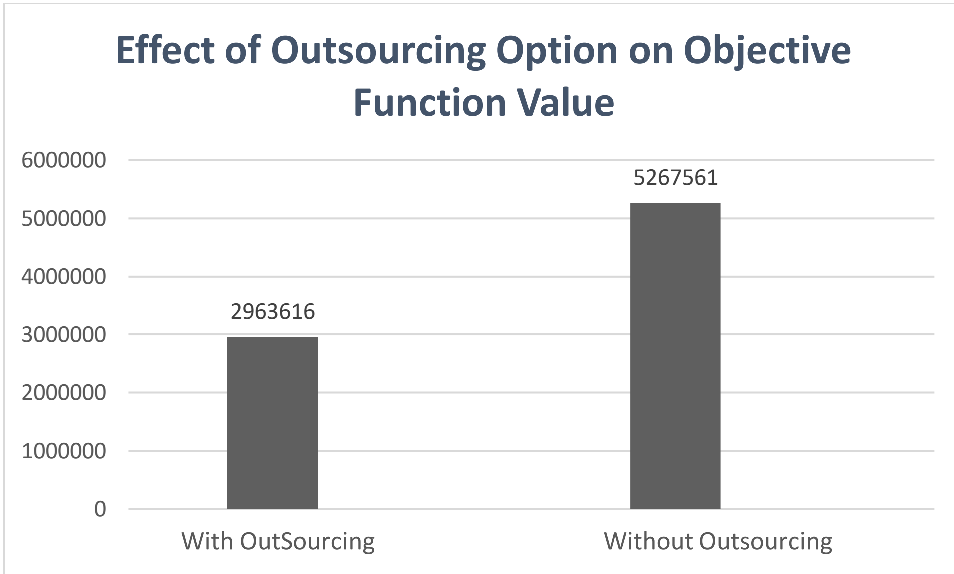

Fig 7. Effect of outsourcing option versus objective function value

5- Conclusion and future research

In this paper, 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 incorporates several recovery options such as recycling, refurbishing, buck recycling, repair, and reuse 'as is' to design a holistic sustainable manufacturing enterprise. Iinvestigation on the large-scale problems of the proposed model and deriving solution methodologies for them is another direction for the future extension of this research.

References

Aalaei, A., & Davoudpour, H. (2017). A robust optimization model for cellular manufacturing system into supply chain management. *International Journal of Production Economics*, *183*, 667-679.

Ahkioon, S., Bulgak, A. A., & Bektas, T. (2009). Cellular manufacturing systems design with routing flexibility, machine procurement, production planning and dynamic system reconfiguration. *International Journal of Production Research*, *47*(6), 1573-1600.

Aljuneidi, T., & Bulgak, A. A. (2020). Carbon footprint for designing reverse logistics network with hybrid manufacturing-remanufacturing systems. *Journal of Remanufacturing*, *10*(2), 107-126.

Aljuneidi, T., & Bulgak, A. A. (2016). Design of cellular manufacturing systems considering dynamic production planning and worker assignments. *Journal of Mathematics and System Science*, *6*, 1-15.

Aljuneidi, T., & Bulgak, A. A. (2016). A mathematical model for designing reconfigurable cellular hybrid manufacturing-remanufacturing systems. *The International Journal of Advanced Manufacturing Technology*, *87*(5), 1585-1596.

Aljuneidi, T., & Bulgak, A. A. (2015). Dynamic Cellular Remanufacturing System (DCRS) Design. *International Journal of Industrial and Manufacturing Engineering*, *9*(5), 859-863.

Badiru, A. B. (2010). The many languages of sustainability: IE's should push for better resource utilization across all fields. *Industrial Engineer*, *42*(11), 30-35.

Baki, M. F., Chaouch, B. A., & Abdul-Kader, W. (2014). A heuristic solution procedure for the dynamic lot sizing problem with remanufacturing and product recovery. *Computers & Operations Research*, *43*, 225-236.

Balakrishnan, J., & Cheng, C. H. (2007). Multi-period planning and uncertainty issues in cellular manufacturing: A review and future directions. *European journal of operational research*, *177*(1), 281-309.

Boukherroub, T., Bouchery, Y., Corbett, C. J., Fransoo, J. C., & Tan, T. (2017). Carbon footprinting in supply chains. In *Sustainable Supply Chains* (pp. 43-64). Springer, Cham.

Bulgak, A. A., & Bektas, T. (2009). Integrated cellular manufacturing systems design with production planning and dynamic system reconfiguration. *European journal of operational research*, *192*(2), 414-428.

Chen, M., & Abrishami, P. (2014). A mathematical model for production planning in hybrid manufacturing-remanufacturing systems. *The International Journal of Advanced Manufacturing Technology*, *71*(5-8), 1187-1196.

Chen, M., & Cao, D. (2004). Coordinating production planning in cellular manufacturing environment using Tabu search. *Computers & Industrial Engineering*, *46*(3), 571-588.

Defersha, F. M., & Chen, M. (2008). A linear programming embedded genetic algorithm for an integrated cell formation and lot sizing considering product quality. *European Journal of Operational Research*, *187*(1), 46-69.

Defersha, F. M., & Chen, M. (2008). A parallel genetic algorithm for dynamic cell formation in cellular manufacturing systems. *International Journal of Production Research*, *46*(22), 6389-6413.

Defersha, F. M., & Chen, M. (2006). A comprehensive mathematical model for the design of cellular manufacturing systems. *International Journal of Production Economics*, *103*(2), 767-783.

Demirel, N. Ö., & Gökçen, H. (2008). A mixed integer programming model for remanufacturing in reverse logistics environment. *The International Journal of Advanced Manufacturing Technology*, *39*(11-12), 1197-1206.

Doh, H. H., & Lee, D. H. (2010). Generic production planning model for remanufacturing systems. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, *224*(1), 159-168.

Egilmez, G., Singh, S., & Ozguner, O. (2017). Cell formation in a cellular manufacturing system under uncertain demand and processing times: a stochastic genetic algorithm approach. *International Journal of Services and Operations Management*, *26*(2), 162-185.

Eguia, I., Racero, J., Guerrero, F., & Lozano, S. (2013). Cell formation and scheduling of part families for reconfigurable cellular manufacturing systems using Tabu search. *Simulation*, *89*(9), 1056-1072.

Fang, C., Liu, X., Pardalos, P. M., Long, J., Pei, J., & Zuo, C. (2017). A stochastic production planning problem in hybrid manufacturing and remanufacturing systems with resource capacity planning. *Journal of Global Optimization*, *68*(4), 851-878.

Forghani, K., & Fatemi Ghomi, S. M. T. (2019). A queuing theory-based approach to designing cellular manufacturing systems. *Scientia Iranica*, *26*(3), 1865-1880.

Garbie, I. H. (2013). DFSME: design for sustainable manufacturing enterprises (an economic viewpoint). *International Journal of Production Research*, *51*(2), 479-503.

Golmohammadi, A., Asadi, A., Amiri, Z., & Behzad, M. (2018). Design of a facility layout problem in cellular manufacturing systems with stochastic demands. *Management Science Letters*, *8*(11), 1133-1148.

Guo, J., & Ya, G. (2015). Optimal strategies for manufacturing/remanufacturing system with the consideration of recycled products. *Computers & Industrial Engineering*, *89*, 226-234.

Hasanov, P., Jaber, M. Y., & Zolfaghari, S. (2012). Production, remanufacturing and waste disposal models for the cases of pure and partial backordering. *Applied Mathematical Modelling*, *36*(11), 5249-5261.

Kishawy, H. A., Hegab, H., & Saad, E. (2018). Design for sustainable manufacturing: Approach, implementation, and assessment. *Sustainability*, *10*(10), 3604.

Jayakumar, V., & Raju, R. (2010). An adaptive cellular manufacturing system design with routing flexibility and dynamic system reconfiguration. *European Journal of Scientific Research*, *47*(4), 595-611.

Jayal, A. D., Badurdeen, F., Dillon Jr, O. W., & Jawahir, I. S. (2010). Sustainable manufacturing: Modeling and optimization challenges at the product, process and system levels. *CIRP Journal of Manufacturing Science and Technology*, *2*(3), 144-152.

Jeihoonian, M., Zanjani, M. K., & Gendreau, M. (2017). Closed-loop supply chain network design under uncertain quality status: Case of durable products. *International Journal of Production Economics*, *183*, 470-486.

Kim, E., Saghafian, S., & Van Oyen, M. P. (2013). Joint control of production, remanufacturing, and disposal activities in a hybrid manufacturing–remanufacturing system. *European Journal of Operational Research*, *231*(2), 337-348.

Koren, Y., & Shpitalni, M. (2010). Design of reconfigurable manufacturing systems. *Journal of manufacturing systems*, *29*(4), 130-141.

Landers, R. G., Min, B. K., & Koren, Y. (2001). Reconfigurable machine tools. *CIRP Annals*, *50*(1), 269-274.

Liu, W., Ma, W., Hu, Y., Jin, M., Li, K., Chang, X., & Yu, X. (2019). Production planning for stochastic manufacturing/remanufacturing system with demand substitution using a hybrid ant colony system algorithm. *Journal of Cleaner Production*, *213*, 999-1010.

Mahdavi, I., Aalaei, A., Paydar, M. M., & Solimanpur, M. (2010). Designing a mathematical model for dynamic cellular manufacturing systems considering production planning and worker assignment. *Computers & Mathematics with Applications*, *60*(4), 1014-1025.

Mahootchi, M., Forghani, K., & Abdollahi Kamran, M. (2018). A two-stage stochastic model for designing cellular manufacturing systems with simultaneous multiple processing routes and subcontracting. *Scientia Iranica*, *25*(5), 2824-2837.

Mutha, A., & Pokharel, S. (2009). Strategic network design for reverse logistics and remanufacturing using new and old product modules. *Computers & Industrial Engineering*, *56*(1), 334-346.

Niakan, F., Baboli, A., Moyaux, T., & Botta-Genoulaz, V. (2016). A bi-objective model in sustainable dynamic cell formation problem with skill-based worker assignment. *Journal of Manufacturing Systems*, *38*, 46-62.

Purcheck, G. F. (1975). A mathematical classification as a basis for the design of group-technology production cells. *Production Engineer*, *54*(1), 35-48.

Raoofpanah, H., Ghezavati, V., & Tavakkoli-Moghaddam, R. (2019). Solving a new robust green cellular manufacturing problem with environmental issues under uncertainty using Benders decomposition. *Engineering Optimization*, *51*(7), 1229-1250.

Sharifi, S., Chauhan, S. S., & Bhuiyan, N. (2012). Reducing setup time in manufacturing cells in a JIT environment. In *Advanced Materials Research* (Vol. 488, pp. 1134-1137). Trans Tech Publications Ltd.

Soolaki, M., Arkat, J., & Ahmadizar, F. (2018). Modeling the Trade-off between Manufacturing Cell Design and Supply Chain Design. *International Journal of Engineering*, *31*(4), 640-647.

Tavakkoli-Moghaddam, R., Aryanezhad, M. B., Safaei, N., & Azaron, A. (2005). Solving a dynamic cell formation problem using metaheuristics. *Applied Mathematics and Computation*, *170*(2), 761-780.

Tavakkoli-Moghaddam, R., Safaei, N., & Babakhani, M. (2005, October). Solving a dynamic cell formation problem with machine cost and alternative process plan by memetic algorithms. In *International Symposium on Stochastic Algorithms* (pp. 213-227). Springer, Berlin, Heidelberg.

Tavakkoli-Moghaddam, R., Safaei, N., & Sassani, F. (2008). A new solution for a dynamic cell formation problem with alternative routing and machine costs using simulated annealing. *Journal of the Operational Research Society*, *59*(4), 443-454.

Wang, J., Zhao, J., & Wang, X. (2011). Optimum policy in hybrid manufacturing/remanufacturing system. *Computers & Industrial Engineering*, *60*(3), 411-419.

www.leandro-coelho.com/linearization-product-variables/

www.rlmagazine.com/edition74p24.php