Energy Sustainability in Changeable Manufacturing Systems

A Thesis
SUBMITTED TO THE FACULTY OF
UNIVERSITY OF MINNESOTA
BY

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IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF MASTER OF SCIENCE IN ENGINEERING
MANAGEMENT

Adviser: Dr. Tarek AlGeddawy

October 2017

Acknowledgement

I would like to take this opportunity to acknowledge all who have helped, assisted and supported me in the completion of this thesis.

I would like to primarily thank my adviser Dr. Tarek AlGeddawy for his precious guidance and support in this research over the past two years.

I would also like to thank my thesis examining committee, Dr. Hongyi Chen and Dr. Mary Christiansen for their time and insightful comments and recommendations.

Finally, I must express my gratitude to my husband, my parents and my brother, who have always been supporting and encouraging me, especially in the past two years. I would have never been able to complete this thesis without their love and support.

Abstract

In a dynamic production environment, not only the product portfolio and demands are varying throughout a multi-period horizon, but also the economic aspects of the environment, such as energy pricing, change with time. The thesis of this work states that energy price fluctuation has a considerable optimizable effect on manufacturing system structural and operational decisions. This work progressively presents three novel linear mathematical models to optimize that effect.

In the first step, a novel basic linear mixed integer mathematical model is proposed to maximize the sustainability of changeable manufacturing systems (MSCM) on the operational level. The model focuses on three factors, which are the change pattern in energy prices throughout the day, the transportation cost of jobs between machines, and the setup cost of each machine, which is dependent on the job sequence. The model output is a system configuration plan, indicating arrangement of machines in the system, and the sequence of jobs, which need to be produced on one day. It is solved by CPLEX solver in GAMS software for nine different problem sizes. The new LMI model finds the optimum configuration plan and job sequence in a reasonable time, which illustrates the efficiency and practicality of the proposed model.

In the second step, a new linear mathematical model is presented to maximize the sustainability of changeable manufacturing systems on the structural level (MSSCM) by selecting the layout reconfiguration and material handling system in each period. It is solved by CPLEX solver in GAMS software to analyze influence of energy pricing and demand fluctuation on system convertibility and scalability, which can affect layout configuration selection.

In the last step, a novel mixed integer linear mathematical model (MILTEC) is presented to maximize the sustainability of RMS on both the structural and operational levels. The system configuration planning in each period of time consists of machines layout and task scheduling which are the most interrelated decisions on the system level. The novel aspect of the presented model is the consideration of energy sustainability concurrently with system configuration and task scheduling decisions in a changing manufacturing environment. The model objective is to minimize total costs of energy consumption, system reconfiguration throughout the planning horizon, and part transportation between machines, which all depend on fluctuations in energy pricing and demand during different periods of time. Several case studies are solved by GAMS Software using the branch-and-bound technique to illustrate the performance of the presented model and analyze its sensitivity to the volatility of energy pricing and demand and their effect on system changeability. An efficient genetic algorithm (GA) has been developed to solve the proposed model in larger scale due to its NP-hardness (non-deterministic polynomial-time hardness). The results are compared to GAMS to validate the developed GA. It shows that the proposed GA finds near-optimal solutions in 70% shorter time than GAMS on average. Different examples are also solved resulting in negligible differences between solutions in several runs of each example to verify the efficiency of the proposed GA.

Table of Contents

List of Tables

List of Figures

CHAPTER 1

INTRODUCTION

Regarding today's fast-changing market challenges such as customer, demand fluctuations, fast growing technologies, and increasing attention to environmental sustainability, manufacturing companies must make decisions in deferent levels to reinforce their ability to upgrade and change their manufacturing systems to survive in the market competition. In this chapter, decisions levels in manufacturing systems particularly in changeable manufacturing systems (CMS), its enablers, and sustainability related decisions in CMS, which is the main objective of this research, are discussed.

Changeability can be gained at different levels including operative, structural, and strategic levels [1]. CMS configuration is a structural level decision, referring to reconfigure a whole production area to the new one in order to produce new product portfolio by mid-term changes in the manufacturing process, layout design, and material handling systems. While sustainability related decisions in CMS is a part of the operational level of decisions along with other factors like sequencing and scheduling decisions in manufacturing systems.

1.1. Decision Levels in Manufacturing Systems

There have been multiple paradigm shifts in manufacturing systems. First, there was the shift from dedicated manufacturing systems (DMS) to flexible manufacturing systems (FMS) by focusing on group technology and creating product families [2]. Then the shift from FMS to changeable manufacturing systems (CMS) to quickly respond to changes in market demand and the expansion of product variety by reconfiguring the manufacturing system in the most cost-effective way. The level of this goal achievement depends on the degree of the following characteristics: convertibility, scalability, modularity, mobility and reconfiguration speed [3]. Convertibility indicates the functionality reconfiguration level to produce different types of products or change the current product family to the new one. The changeable manufacturing system improves scalability that is changing production rates in response to demand fluctuation. Modularity is a primary feature of the changeable layout that greatly helps to change operational requirements. Mobility improves flexibility in changing operational routes by relocating machines and tools. Reconfiguration speed is about the required time for transition from the current configuration to the next. It is required for setting up machines, rearrangement of machines, tools, and adapting material handling systems [3].

Reconfiguration can be referred as changing different aspects of the manufacturing system including routing, scheduling, layout configuration, machines settings, and material handling systems [4]. While FMS responded to changing market requirements through adapting scheduling and tooling by fixed hardware and programmable software, CMS responded to demand fluctuation by changing hardware and software modules [2]. Reconfiguration design can be conducted at different levels such as system level, machine level, and planning and control level. Adding, relocating and removing machines are performed at the system level while adding an extra spindle or axes of motion are performed at the machine level. In addition, integrating extended controls to the current control system is conducted at the control level [5].

These different aspects of the reconfigurations can be categorized as physical and logical ones, where physical changes in tools and equipment and rearrangement of machines are defined as physical reconfiguration and changes in routing, scheduling and sequencing are defined as logical reconfiguration [1].

There are mainly six structuring levels of a manufacturing system, which are identified from a process and product level aspects, including network, factory, segment, system, cell, and workstation as shown in Figure 1 [1]. When a system can change its performance and behavior without reconfiguration, the ability is traditionally interpreted as flexibility. While the ability to change performance and behavior by the system reconfiguration is recognized as reconfigurability. However, these definitions completely depend on how the system boundaries are defined. Therefore, there is no general statement to differentiate between flexibility and reconfigurability as types of changeability [1].

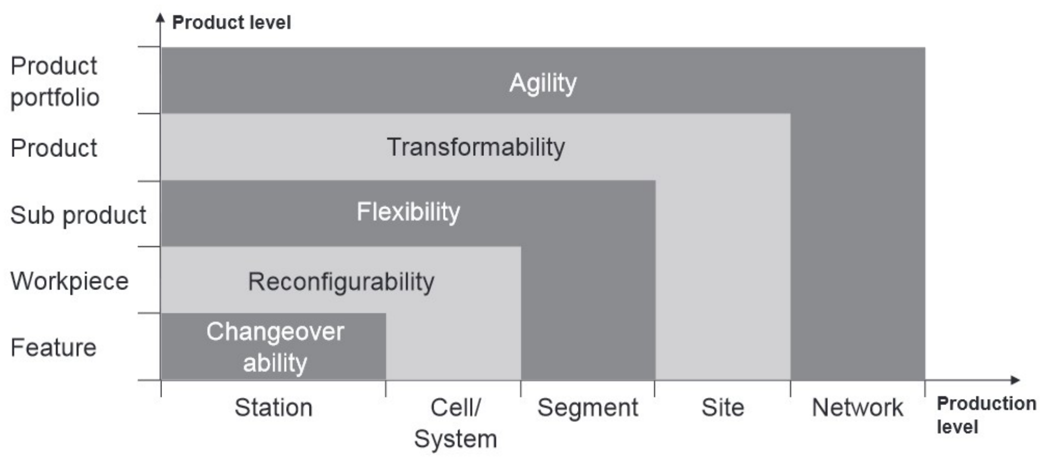

Figure 1-Classes of Factory Changeability. Adapted from "Changeable Manufacturing - Classification, Design and Operation" by Wiendahl et al. CIRP Ann - Manuf Technol 2007; 56:783–809. Copyright 2007 by Elsevier. Adapted with permission, License No. 414716042501.

The operative ability of a workstation to do specific operations on a particular part or subassembly at any chosen moment with minimal effort and delay can be defined as changeover ability. Reconfigurability defines the operative ability to shift into a known family of workpieces or subassemblies by changing functional elements with minimal effort and delay in a manufacturing system. Flexibility designates the structural ability of an entire manufacturing area to swap to new families of components but similar to the last one with reasonable time and effort, through logical reconfiguration such as manufacturing processes the flow of materials and logistical systems.

Transformability refers to the structural ability of a whole factory structure to change to another product family. Different aspects of structural interventions in both production and logistic systems are required for transformability, such as changing the structure of organization, processes, and facilities. The strategic ability of a company to initiate new markets, develop an essential product or introduce new services, and expand its manufacturing capacity is interpreted as agility.

Therefore, it can be concluded that "Reconfigurability" is a term, which is limited to levels below factory level, while transformability and agility are described as changeability classes for factory level and above.

1.2. Sustainability Related Decisions in Manufacturing Systems

Sustainability is a multifaceted concept. The most famous definition belongs to the UN Bruntland commission: "sustainable development is development that meets the needs of the present without compromising the ability of future generations to meet their own needs." Sustainable development objectives focus on three areas including economic development, social development, and environmental protection referring to the 2005 World Summit on Social Development [6].

Reconfiguration plays a significant role in manufacturing strategy to improve the environmental sustainability of the system in terms of energy consumption along with economic development. While several studies have been conducted on the RMS reconfiguration planning to minimize reconfiguration cost and complexity, and to maximize reliability and availability of the manufacturing system, there are only few research works that consider sustainability aspects of the RMS. Due to the increasing

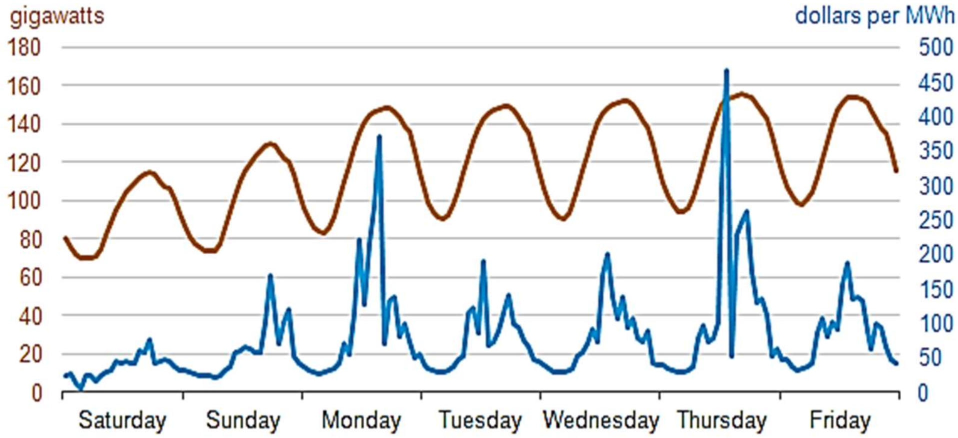

Figure 2-Hourly real-time energy prices responding to the hourly demand (Source: US Energy Information Administration, https://www.eia.gov/todayinenergy/detail.php?id=12711)

attention in environmental sustainability, companies tend to improve their manufacturing systems performance in order to optimize energy consumption. There exists very rich literature on energy-efficient manufacturing processes and machinery [7]. The major focus of energy saving in manufacturing has been accomplished by improving machine physical performance or the manufacturing processes individually [8], however, there is also a great opportunity for energy saving by considering a system-level approach, which is discussed in this thesis.

Electricity pricing is greatly dependent on demand and time of use since the electricity industry should adjust the supply in real time to response demand due to lack of large-scale storage.

There are different energy demand response programs controlling unstable energy pricing. One of the most successful programs, which has been employed in some countries such as U.S.A, to reduce electricity consumption cost is the time-of-use (TOU) pricing [9].

Electricity demand changes hourly, monthly, and seasonally. It goes up in the summer and winter and goes down in the spring and fall. Increasing electricity demand leads to raising the price and vice versa, decreasing the demand reduces the price.

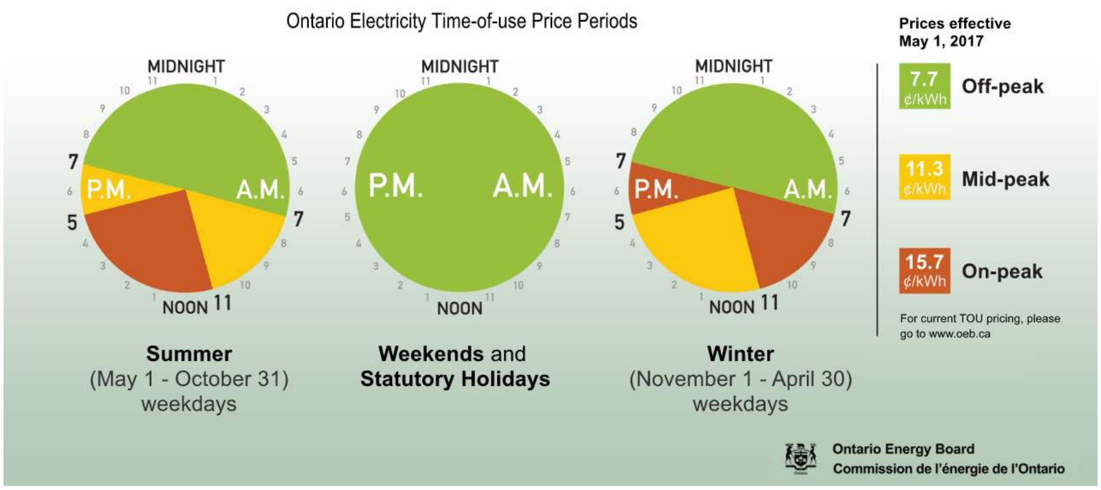

Figure 3. A sample of TOU electricity price (Ontario energy Board)

Hourly real-time energy prices responding to the hourly demand throughout the week are shown in Figure 2. It depicts energy pricing is much more unstable. There are several studies through the last decade which show the barriers and the policies of energy efficiency program implementation [10,11]. Demand-Side Management (DSM) considers peak decreasing and load shifting to off-peak from on-peak energy tariff rates in order to reduce energy costs [12]. Great endeavors in DSM have resulted in many benefits in economic and environmental points of view. A variety of strategies have been implemented in some countries to decrease energy consumption costs such as adopting TOU pricing with great differences between on-peak and off-peak tariff rate [13]. The changes in energy prices play a crucial role in energy consumption costs.

A full day is divided into the on-peak and off-peak periods in most cases of TOU structure. Also, sometimes it is divided into three time periods considering a mid-peak period too. Daylight hours are covered by the on- and mid-peak periods while night time hours are dedicated to the off-peak period shown in Figure 3. All these period times are defined based on the Local Standard Time. For instance, according to the survey of the TOU electricity pricing programs targeting industrial customers in the

U.S conducted by Wang and Li, unique on-, mid-, off- peak periods with different rates of energy price are defined for each state of U.S.A[9].

1.3. Thesis Statement

This research is focused on a changeable manufacturing system considering the fluctuating energy pricing to analyze its role on reconfiguration decisions. To consider changing electricity pricing in CMS, it should be noted that the reconfiguration cost does not only depend on the degree of system changeability but also can depend on the time during which it is performed since electricity pricing changes within and between periods of time. In this regard, this thesis follows three levels including operational, structural, and comprehensive levels in an evolutionary basis considering the influence of changing energy pricing in reconfiguration decisions.

1.4. Thesis Outline

This thesis is organized into 7 chapters. The following chapter presents a literature review of changeable manufacturing systems at both physical and logical levels. In addition to studies specifically focused on sustainability in CMS is also reviewed.

Chapter 3 discusses the research methodology. The proposed mathematical models in different levels of changeability are presented.

Chapter 4 presents example problems of each model, which are solved by GAMS software. The results are analyzed.

Chapter 5 introduces a Genetic Algorithm approach to executing the final model on larger size problems. A design of experiments is also presented to control the performance of the developed GA.

Chapter 6 presents and analyzes results of several example problems to demonstrate the efficiency of the presented GA.

Chapter 7 includes the concluding remarks and future research directions.

CHAPTER 2

Literature Review

2.1. Changeable Manufacturing Systems

Researchers and practitioners have significantly focused on changeable manufacturing systems in recent years due to their ability to quickly respond to changes at the lowest cost compared to other manufacturing systems [14]. In the 1990s, the changeable manufacturing system was first proposed to efficiently respond to changes in demand due to internal and external uncertainties [15]. The concept of changeability in six structuring levels of manufacturing system has been comprehensively considered in recent years [1], [16]. The influence of different changing drivers of global manufacturing structure on the economy such as products, markets, new technologies, etc. have been broadly investigated [1]. Wiendahl et al. introduced four main external factors and four internal ones which affect the global economy including markets, political factors, finance, and environment as external drivers, and human resources, products, new methods, and networked structures as internal drivers. They stated that manufacturing firms must identify and understand their main change drivers, the objects of changeability and the appropriate degree of change to conduct the required and proper actions to adapt the change in a reasonable time. Different changeability enablers have been studied. They increase the system responsiveness and mitigate the consequence of changes in logical and physical levels of manufacturing systems [1], [17], [18]. The physical and logical features that make a factory changeable are defined as changeability enablers. Wiendahl et al. presented an overview of changeability enablers in both logical and physical levels of manufacturing systems. They considered reconfigurable process planning (RPP) and adaptive production planning and control (APPC) in the logical system. Reconfigurable manufacturing system (RMS), reconfigurable assembly system (RAS), and transformable factory (TRF) are considered in the physical system.

Characteristics of changeability including convertibility, scalability, modularity, integrability, customization, and diagnosibility are discussed in detail as guidelines of reconfigurable manufacturing system design [15]. Modularity helps the system to exchange, upgrade, and integrate components easier to provide new applications. Convertibility is the characteristic of the system that switches production between two parts of a family and consequently change a tool, or either adding or removing machines in the system in an efficient way [4]. Scalability of capacity is another feature of RMS. It is an ability to change the system to increase productivity to meet the new demand through adding, removing tools and machines. Integrability is a key to design reconfigurable systems [4]. Integration rules allow us to identify parts modules based on similarity in features and their corresponding machines cells based on similarity in processes. Customization is the main characteristic that differentiates RMS from FMS. It results in cost reduction in the system. It is the ability of a system to produce a part family instead of just a single part which needs utilization of multiple tools on a single machine, integrated control modules on multiple processes and tools [4]. Diagnosability is the ability to notice machine failure and recognize the causes of failure on produced part quality. This feature is vital in RMS since the reconfigured system requires to be quickly tuned [4]. The effect of all changeability characteristics on different manufacturing system levels has been analyzed [19], [20]. On the manufacturing level, RMS must include all 6 mentioned reconfigurability characteristics (enablers) to gain the desirable flexibility to address the fluctuation in demand. It is stated that customization, convertibility, and scalability are crucial features of RMS and the other three characteristics are supporting ones on this level [1]. On the assembly level, two more features (enablers) including mobility and automatability are required along with the six enablers for RMS. On the factory level, five enablers are required for RMS including universality, scalability, modularity, mobility, and compatibility which affect the system's ability to adapt to fluctuations [1]. All characteristics have to be considered in every aspect of reconfigurable manufacturing systems at both physical and logical levels to design a system that is able to reconfigure process planning and control, the design of the system layout, and the machine or tool design [21].

A comprehensive literature review in reconfigurable manufacturing systems has been conducted by Anderson et al. in 2015 [22]. Over 170 papers are reviewed and classified according the six structuring levels of manufacturing system. The authors summarized the number of papers and research issues at each level.

According this review, about two third of literature on reconfigurable manufacturing belongs to the system level and less than one third belongs to the workstation level. The primary issues on reconfigurable systems are related to logical types of reconfiguration including process planning, or optimal reconfiguration selection. Physical type of reconfiguration has been mainly considered in the workstation level to design reconfigurable machines and tools.

Beside the literature review by Anderson et al., another classification of the recent literature review in this thesis is conducted based on three different domains of configurations including process planning and control, design of the system (layout), and the machine or tool design. Furthermore, papers focused on energy sustainability in this area are reviewed.

2.1.1. Process / production planning and control

Galan focused on clustering products into families and scheduling only part families in RMS through developing meta heuristics such as tabu search and ant colony algorithms [23]. Meng developed a model for reconfigurable processes of manufacturing system through using colored timed object-oriented Petri nets which integrates two methods including stepwise refinement concept and Petri nets [24]. Abbasi and Houshmand proposed a methodology to efficiently change scalable production capacities and determine lot size, corresponding tasks routing and production configuration through a mixed integer nonlinear programming model to response to fluctuation in demand [25]. Azab and Gomma developed an integer model and proposed a genetic algorithm for operation scheduling in RMS with aim of changeover cost minimization [26]. Yu et al. prsented a practical priority rule-based approach in scheduling for a reconfigurable job shop manufacturing system with a limited number of fixtures [27]. Musharavati and Hamouda presented a novel metaheuristic algorithm, integrating simulated annealing and concept of knowledge exploitation and parallelism to determine optimum process planning in RMS [28]. Chaube et al. developed an approach using an adapted NSGA-2 algorithm to come up with the dynamic process plan for minimizing total cost of RMS. The necessities of the components/products are evaluated which are then considered by the functionality (other configurations and features) suggested by machines to reduce the manufacturing cost and time [21]. Azab and Naderi determined job scheduling and system reconfiguration plan through developing a new mathematical model and using simulated annealing to effectively minimize makespan and solve the problem [29].

2.1.2. Machine/tool design

Bensmaine et al. studied RMS (i.e., the selection of alternated reconfigurable machines amongst an available set) according to products characteristics and reconfigurable machines abilities [30]. They presented an adapted form of the non-dominated sorting genetic algorithm to find the optimum solution with aim of minimizing the total cost and total completion time simultaneously. Guan et al. proposed a new model (a revised electromagnetism-like mechanism) in RMS to design the layout applying automated guided vehicle with aim of minimizing the total material handling cost [30]. Azab et al. presented a novel model in RMS to determine processes and set points to change manufacturing system configurations based on the supply and essential machines and system modules for reconfiguration [31]. The framework mapped between reconfiguration enablers and ones for sustainability is presented. Reconfiguration of manufacturing systems is considered as a controller to minimize the differentiates between reconfigurability and sustainability costs.

2.1.3. Layout

There are several studies to design of the layout configuration in dynamic cellular manufacturing systems. Ahkioon et al. proposed a mixed-integer programming model to design reconfigurable cellular manufacturing systems determining multi-period production planning, layout reconfiguration and operation sequence, machines purchasing, duplicate machines, and machine capacity [32]. Saidi-Mehrabad and Safaei applied a neural networks approach to solve the proposed dynamic cell formation model to minimize reconfiguration cost including machine cost, intra and inter cell transportation costs [33]. Ahkioon et al. proposed an integrated approach for CMS design applying non-linear mixed-integer programming model to determine production planning and system reconfiguration including alternate process routings, operation scheduling, machine procurement strategy, machine capacity [34]. Safaei and Tavakkoli-Moghaddam proposed integrated dynamic cell formation and production planning to minimize machine purchasing, layout reconfiguration, inter/intra-cell movement and outsourcing costs [35]. They considered the result of the trade-off between production and out sourcing costs on making decision for the cell reconfiguration. Kia et al. developed a new mixed-integer non-linear programming model to design the layout of a dynamic cellular manufacturing system through determining cell formation, group layout to meet different products demand in multi-periods of time [36]. Rafiee et al. proposed a novel mathematical model integrating cell design and inventory lot sizing problems to minimize total cost associated with production and layout reconfiguration [37]. They presented a comprehensive model to determine possible routings, machine capacity constraint, operations scheduling, cell size limitation, machine breakdowns while minimizing the total cost of machine purchasing, cell reconfiguration, maintenance activities, intra-cell and inter-cell movement of martials, outsourcing, machine process, completed and incomplete parts inventory, and scrap and imperfect parts. Khedri Liraviasl et al. developed a framework for reconfigurable manufacturing systems integrating hybridized Agent based and Discrete-Event simulation algorithm. They applied different modification in the system to analyze the evolutionary behavior of the simulation model. The main advantages of the proposed framework are decentralized control and cooperative decision making taking benefit of flexible response to system changes [38].

2.2. Energy Sustainability in Manufacturing Systems

The rich literature on energy-efficient manufacturing processes and machinery is mainly focused on improving machine's physical performance or the manufacturing processes individually [7],[8]. Mouzon et al developed a methodology for a single CNC machine scheduling focusing the non-bottleneck machines idle to optimize total energy consumption [39]. Subai et al investigated on hoist scheduling problem to minimize energy consumption and waste resulted by surface treatment processes [40]. Wang et al. developed an optimization procedure for vehicle scheduling problem in an automotive paint shop to minimize energy consumption through finding the optimal batch and scheduling policies [41]. Mori et al. proposed a practical approach on machine tools to monitor the energy consumption [42]. Diaz et al explored the electrical energy recycle by spindle [43].There are several studies focused on changing machining processes and performances through using CNC or a programmable logic controller [42], [44], [45] developing cutting strategies, changing machine setting such as axis and spindle acceleration to optimize energy consumption [44].

According to increasing attention to global environmental sustainability, energy consumption efficiency has been started to consider in RMS. The limited literature of RMS considering sustainability is also mainly related to the logical type of reconfigurations including tools design and process planning. Carvalhoa & Gomes proposed and applied a new methodology utilizing computer numerical control (CNC) or a programmable logic controller (PLC) to improve the energy efficiency of machine tools and equipment in three flexible automotive machining systems [46]. Duflou et al. presented a comprehensive literature review in the domain of discrete part manufacturing focused on energy and resource efficiency approaches and techniques

[47]. Wang et al. presented a two-stages systematic approach for milling process planning and scheduling optimization to increase flexibility, responsiveness, and energy efficiency in a dynamic job shop floor [48]. In the process stage, crucial operational factors for milling a component are improved adaptively to reach multiple goals and meet limitations, i.e., energy sustainability of the milling process and throughput as goals and surface quality as a limitation. In the system stage, setting up machining features, sequencing operations and scheduling mixed parts on different machines are optimized to improve energy efficiency and reduce makespan in the whole shop floor. Choi and Xirouchakis presented a two-stage stochastic approach in a reconfigurable manufacturing system considering a linear holistic production planning model to analyze the influence of different types of material handling systems on the energy consumption [49]. The objectives of the model are minimizing energy consumption while maximizing the throughput. In the other study, they developed a novel mathematical model for production planning problem considering different energy consumption in a very automated manufacturing system. The system includes several interrelated sub-systems such as material/tool handling, processing, and cooling/ lubricant systems. They proposed a linear mathematical model on a flexible manufacturing system finding optimum multiple process plans with aim of minimizing energy consumption, inventory and backorder costs simultaneously in a system level [50]. Different mathematical models and heuristic approaches are presented for scheduling problems to consider shifting production planning from the peak power load with aim of energy consumption minimization [8], [51], [52]. Pellegrinellia et al. proposed an integrated model for process planning and pallet configuration to minimize energy consumption and production cost and maximizing the system throughput [53]. Literature review of RMS shows that research work on sustainability in RMS is very

limited, and a research gap on the energy efficiency of reconfigurable manufacturing systems related to layout configuration design exists.

Fifteen recent papers that are the most related studies to this thesis in terms of domain of study, objectives, or the applied methodology are presented in table 1. The year of the paper, the domain of study including process planning and control, design of the system (layout), the machine or tool design, and energy sustainability, and the methodology applied are indicated for each paper in this table.

Table 1-Literature Review Summary

Author(s)	Year	Classification				Methodology					
		Machine /tools	Layout	Process	Sustainability	Math model	Framework	optimization	Meta-heuristic	Simulation	Stochastic
Choi & Xirouchakis[52]	2015	•		•	•	•					•
K. Khedri Liraviasl et al.[45]	2015		•	•			•			•	
Azab & Naderi[38]	2015			•		•		•			
C. Plehn et al.[12]	2015			•		•	•				•
Carvalhoa & Gomes [47]	2015	•			•		•				
S.Wang et al.[49]	2015	•		•	•		•		•		
Choi & Xirouchakis[51]	2014	•		•	•	•		•			
Ossama et al.[55]	2014		•	•		•		•			
Azab et al.[30]	2013	•		•	•		•				
Jae-Min Yu et. al[37]	2013	•		•						•	
T. AlGeddawy et al.	2012		•	•			•				
A. Chaube et. al[5]	2012	•	•	•		•			•		
Pellegrinellia et al.[53]	2012	•	•	•	•	•	•	•			
R. Kia et al.[46]	2012		•	•		•			•		
T. AlGeddawy & H. Elmaraghy	2009			•			•				

2.3. Conclusion

According the literature review is discussed above, it is concluded that lower levels of manufacturing systems problems mainly considering physical reconfiguration, while higher levels of manufacturing system problems primarily focus on logical reconfiguration. Furthermore, most of researches in changeable manufacturing systems area focused on the lower levels of CMS which is the workstation, cell, and systems. However, reconfiguration on shop-floor has many implications for the whole system related to its layout, structure, and logistical configuration.

In addition, literature review of CMS shows that research work on sustainability in CMS is very limited, and a research gap on the energy efficiency of reconfigurable manufacturing systems related to layout configuration design exists. None of the previous studies have considered the effect of changing energy price simultaneously on the layout configuration and operation schedule decisions.

In this thesis, an integrated multi-period layout planning and scheduling model for sustainable reconfigurable manufacturing systems is developed to analyze the effect of changing energy price on the layout configuration and operation schedule decisions together. The system configuration decisions incorporate design features including purchasing machines, duplicate machines, and machines arrangement at each period, and operation schedule decisions consist of task scheduling, alternate process routings, completion time for each product over the planning horizon. The presented model objectives include the total cost of energy consumption, system reconfiguration, and part transportation between machines, depending on fluctuations in energy pricing and demand during the time, which has not been considered simultaneously before as well.

CHAPTER 3

Methodology

In this thesis, optimization methodology is applied to analyze the influence of changing energy price in reconfiguration decisions. This research follows three steps in an evolutionary basis considering a system changeability in operative and structural levels.

Firstly, a novel basic linear mixed integer mathematical model is proposed to maximize sustainability of the changeable manufacturing system in operative level. The daily production demand of several product variants should be satisfied by corresponding configurations of the manufacturing system according to unstable energy price. System configuration planning consists of machine arrangement and job sequencing. The proposed model considers three main factors that affect system sustainability in the environmental and economic domains, which are, 1) the change pattern in energy prices throughout the day, 2) the transportation cost of jobs between machines, which depends on machines locations in the system, 3) the setup cost of each machine, which is dependent on the job sequence. The model output is a system configuration plan, indicating arrangement of machines in the system, and the sequence of jobs, which need to be produced on one day.

Secondly, the influence of changing energy price in reconfiguration decisions is considered from a bigger-picture perspective. A new linear mixed integer mathematical model is presented to maximize sustainability of reconfigurable manufacturing system on the structural level by selecting the layout reconfiguration and material handling system in a given number of time periods. Different layout configuration consumes different amount of energy to meet the product demand. However, system configuration selection is not only affected by different amount of energy consumption and reconfiguration cost, but also by volatile energy pricing throughout the planning horizon (from hourly changing to seasonal changing). Sustainability is considered by means of selecting energy-efficient and financial resource-saving manufacturing systems. Convertibility and scalability of the system as two of most important characteristics of reconfigurability are considered. The influence of demand fluctuation and volatile energy price on the layout configuration selection is analyzed to minimize the system cost includes reconfiguration cost and energy consumption cost.

Finally, a comprehensive model is proposed to analyze the effect of changing energy pricing in reconfiguration decisions. A novel linear mixed integer mathematical model is presented to maximize energy sustainability of reconfigurable manufacturing systems. Changing demands of different product portfolios should be satisfied during the time by corresponding mid-term reconfigurations of the manufacturing system and adjusting to the changing energy price between and within each period. System configuration planning consists of machine layout and task sequencing which are the most interrelated decisions. Transportation cost also has a great effect on reconfiguration decisions. It is associated with moving parts between machines, which directly depends on distances between machines and product type. Hence, reconfiguring machine layout or process routing from one period to another may result in a high transportation cost, which economically might make the system reconfiguration unreasonable. The proposed model evaluates three costs to improve the system sustainability in the environmental and economic domains, which are, 1) energy consumption cost depending on the change pattern of energy pricing between and within each period, 2) the reconfiguration cost depending on machines arrangement changes between periods, 3) the transportation cost of parts between machines, which depends on machines locations and demand volume in each period. The model output is a system configuration plan, indicating machine layout and the sequence of tasks in each period to meet its product demand. The novel aspect of the presented model is the consideration of energy sustainability concurrently with system configuration and operation schedule decisions in a changing manufacturing environment using a linear mathematical model.

3.1. **The basic model (MSCM)** [54]

A system consists of a number of machines which should be arranged in a closed loop layout as shown in Figure 4. A number of different jobs are required to satisfy the daily production demand. Each job should be processed by a unique set of machines in a specified order. The sequence of required machines for processing each job is given. A job represents the demand of a specific product or product variant. A job requires at least one machine and at most all machines in the line to be finished. There is a unidirectional material handling system to transport work-in-process from one machine to another. A job may need the same machine more than one time to be done. Each job starts processing immediately when the last preceding job processes are finished. Maximum working hours in a day is 12 hours. The energy consumption cost is considered based on the TOU pattern of energy pricing throughout a day.

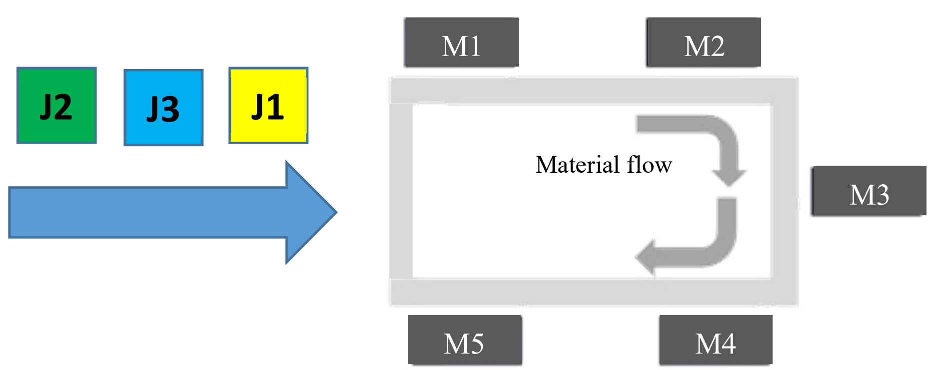

Figure 4- A layout configuration along with job scheduling

A new mixed integer linear mathematical model is presented to minimize the total energy consumption cost, the total transportation cost of jobs between machines and the total set up cost of machines simultaneously. The following notations are used in the mathematical model.

Indexes

m, n: Machine, m= 1,2, …, M, where M is the number of machines

j, i, l: Job, j= 1,2, …, J , where J is the number of jobs

t: Time, t= 1,2, …, T, where T is working time of a day

Parameters

Tp_j: Processing time of job j

E_j: Energy consumption of job j

Ep_t: Energy price in time t

TS_{jmk}: Transportation cost of job j from machine m to machine k

ST_{jim}: Setup cost of machine m for processing job j when job i precedes job j

BM A large number

ε A small number

Decision Variable

x_{mk} Distance between machine m and machine k

y_{ij} Equal to 1 if job i precedes job j, and 0 otherwise

h_{nm} Equal to 1 if machine m precedes machine n in layout

w_{jt} Equal to 1 from beginning of a day to completion time of job j

w'_{jt} Equal to 1 from beginning of a day to start time of job j

q_m Position of machine m (1, 2, …, M)

C_j Completion time of job j

EC_{jt} Energy consumption cost of job j in time t

TEC Total energy consumption cost

SC Total setup cost

TC Total transportation cost

The problem is formulated as follow:

Problem Formulation

$$\boldsymbol{Min\, Tc + SC + TEC} \tag{1}$$

S.T

$$\sum_{m=1}^{M} q_m = \frac{M(M+1)}{2} \tag{2}$$

$$q_m - q_n \geq \varepsilon . h_{nm} - BM . h_{mn} \qquad \forall\, m, n\, ;\, m \neq n \tag{3}$$

$$q_m \geq 1 \qquad \forall\, m \tag{4}$$

$$h_{mn} + h_{nm} = 1 \qquad \forall\, m, n\, ;\, m \neq n \tag{5}$$

$$x_{mn} \leq q_m - q_n + BM(1 - h_{nm}) \qquad \forall\, m, n \tag{6}$$

$$x_{mn} \leq M - x_{nm} + BM(1 - h_{mn}) \qquad \forall\, m, n \tag{7}$$

$$x_{mn} \geq q_m - q_n - BM(1 - h_{nm}) \qquad \forall\, m, n \tag{8}$$

$$\boldsymbol{x_{mn} \geq M - x_{nm} - BM(1 - h_{mn})} \qquad \forall\, \boldsymbol{m, n} \tag{9}$$

$$\boldsymbol{\sum_{j=1}^{J} \sum_{m=1}^{M} \sum_{n=1}^{M} TS_{jmn}.\, x_{mn} \leq TC} \tag{10}$$

$$\boldsymbol{\sum_{i=1}^{J} y_{ij} \leq 1} \qquad \forall\, \boldsymbol{j} \tag{11}$$

$$\boldsymbol{\sum_{j=1}^{J} y_{ij} \leq 1} \qquad \forall\, \boldsymbol{i} \tag{12}$$

$$\boldsymbol{y_{ij} + y_{ji} = 1} \qquad \forall\, \boldsymbol{i, j}\,;\, \boldsymbol{i \neq j} \tag{13}$$

$$\boldsymbol{y_{ij} + y_{jl} + y_{il} \leq 2} \qquad \forall\, \boldsymbol{i, j, l}\,;\, \boldsymbol{i \neq j \neq l} \tag{14}$$

$$\boldsymbol{\sum_{\substack{j=1 \\ j \neq i}}^{J} \sum_{i=1}^{J} y_{ij} = J - 1} \tag{15}$$

$$\boldsymbol{\sum_{m=1}^{M} \sum_{j=1}^{J} \sum_{i=1}^{J} ST_{jim}.\, y_{ij} \leq SC} \tag{16}$$

$$\boldsymbol{C_i + Tp_j - BM\left(1 - y_{ij}\right) \leq C_j} \qquad \forall\, \boldsymbol{i, j}\,;\, \boldsymbol{i \neq j} \tag{17}$$

$$\boldsymbol{Tp_j\left(1 - y_{ij}\right) \leq C_j} \qquad \forall\, \boldsymbol{i, j}\,;\, \boldsymbol{i \neq j} \tag{18}$$

$$\boldsymbol{C_j - t + 1 \leq BM\left(w_{jt}\right)} \qquad \forall\, \boldsymbol{j, t} \tag{19}$$

$$\boldsymbol{C_j - t + 1 - Tp_j \leq BM\left(w'_{jt}\right)} \qquad \forall\, \boldsymbol{j, t} \tag{20}$$

$$\boldsymbol{C_j - t \geq -BM\left(1 - w_{jt}\right)} \qquad \forall\, \boldsymbol{j, t} \tag{21}$$

$$\boldsymbol{C_j - t - Tp_j \geq -BM\left(1 - w'_{jt}\right)} \qquad \forall\, \boldsymbol{j, t} \tag{22}$$

$$\boldsymbol{\left(w_{jt} - w'_{jt}\right).\, Ep_t.\, E_j \leq EC_{jt}} \qquad \forall\, \boldsymbol{j, t} \tag{23}$$

$$\boldsymbol{\sum_{j=1}^{J} \sum_{t=1}^{T} EC_{jt} \leq TEC} \tag{24}$$

Equation (1), represents the objective function addressing minimization of associated costs to energy consumption, sequence-dependent setup of machines and transportation of jobs between machines to find the optimal solution. Equations (2) to (4) guarantee that each machine has a unique position number between set of 1 to M. Equation (5) ensures that sequence of each two machines is unique. Equations (6) to (9) calculate distances between each two machines based on their sequence while production line is closed loop and there is one-way to transport jobs in the line. It should be noted that equations (7) and (9) guarantee that sum of distances from machine m to machine n and vice versa is equal to M. In other words, these equations guarantee machines to be arranged in the closed loop line. Equation (10) computes total transportation cost of jobs between machines. Equations (11) to (14) determine the sequence of jobs and ensures that just a unique job precedes the other job. Equation (15) shows that exactly (J-1) of sequences should be equal to 1 when there are J numbers of jobs. Equation (16) calculates total setup cost which depends on sequence of jobs to proceed. Equations (17) to (18) calculates completion times of jobs. Equations (19) to (22) determine time between start and completion of each job processing. Equations (19) and (23) calculate the energy consumption cost of each job in each hour of processing with help of equations (19) to (23). The last equation calculates total energy consumption cost of production.

3.2. **The second model (MSSCM)** [55],[56]

The second model is a new linear mixed integer mathematical model which maximizes sustainability of the changeable manufacturing systems on the tactical level. The different seasonal production demand of several product should be satisfied by selecting different manufacturing configurations between seasons. It is assumed that there are different product portfolios with different number of products in different seasons. There is a given number of feasible system configuration for each season which meet the demand. The proposed model considers demand fluctuation during seasons and volatile energy price between and within a season that may affect the system configuration selection. The reconfiguration system selection consists of layout configuration and process routings. The layout configuration includes arrangement of machines that needs a unique job scheduling to keep the system performance optimum. Therefore, each layout configuration may have a different job scheduling and consequently different job completion times to meet the demand. Each layout has a number of alternative process routings to produce particular product. It is assumed that different routings consume different amount of energy and energy pricing is volatile during the time. Thus, the average energy price is not the same for different layout configuration during a period of time, since energy price fluctuates during the time and jobs could be completed by different time durations based on what layout configuration is selected.

Convertibility and scalability are considered based on demand variation during seasons and unstable energy price between and within a season. The degree of the system convertibility is evaluated by calculating the reconfiguration cost between seasons and energy consumption cost of the system. Each layout has a particular utilization to meet the seasonal demand. As demand could be varied during a season, the percentage of increasing utilization up to 100% is considered as a degree of the system scalability to response to increased demand. The mathematical model is described in detail as follow:

Indexes

$s = 1, 2, \ldots, S$	Time period, e.g. season

i,j= 1,2,…, L	Layout configuration
p= 1, 2, …, p	Type of product
l= 1, 2, …, L	Process routing

Parameters

C_{is}	The average energy price of layout configuration i in season s
E_{isp}^{l}	Energy consumption of process routing l in layout configuration i in season s to produce p
CA_{isp}^{l}	The maximum capacity of process routing l in layout configuration i in season s to produce p
TC_{ijs}	Reconfiguration cost from layout i in season s to layout j in season s+1
U_{ips}	Utilization of layout configuration i for product p in season s
ic_{is}	Fixed idle cost of layout configuration i in season s
ie_{is}	Energy consumption of layout configuration i during the idle time in season s
D_{ps}	Demand of product p in season s
I_{ps}	Profit per unit of product p in season s
α_{ips}	Probability of (1- U_{ips})% increasing in demand of product p in season s

Decision variables

x_{is}	Binary variable equal to 1 if layout configuration i is selected in season s
y_{ijs}	Binary variable equal to 1 if layout configuration i in season s should be changed to layout configuration j for the next season
N_{isp}^{l}	Number of product p processed by process routing l in layout configuration i in season s

TEC Total energy consumption cost

TIC Total idle cost

TTC Total configuration cost

TP Total profit by scalability

Mathematical formulation

Obj: Minimize

$$\boldsymbol{TEC + TIC + TTC - TP} \tag{1}$$

S.T.

$$\sum_i \boldsymbol{x_{is} = 1} \qquad \forall\, \boldsymbol{s \in S} \tag{2}$$

$$\boldsymbol{x_{is} + x_{j.s+1} - y_{ijs} \leq 1} \qquad \forall \boldsymbol{i.j} \quad \forall \boldsymbol{s}|\ \boldsymbol{s < S} \tag{3}$$

$$\boldsymbol{N^l_{isp} - x_{is}.\ CA^l_{isp} \leq 0} \qquad \forall \boldsymbol{i, s, p, l} \tag{4}$$

$$\sum_l \sum_i \left(\boldsymbol{N^l_{isp}}\right) - \boldsymbol{D_{ps} = 0} \qquad \forall \boldsymbol{p, s} \tag{5}$$

$$\sum_s \sum_i (\boldsymbol{x_{is}.\, E_{is}.\, C_{is}}) - \boldsymbol{TEC} \leq 0 \tag{6}$$

$$\sum_s \sum_i \boldsymbol{x_{is}(ic_{is} + ie_{is}C_{is}) - TIC} \ \leq 0 \tag{7}$$

$$\sum_i \sum_j \sum_s \boldsymbol{y_{ijs}TC_{ijs} - TTC \leq 0} \tag{8}$$

$$\sum_i \sum_m \sum_s \sum_r \boldsymbol{x_{irs}\left(1 - U_{ips}\right)D_{ps}.\, \alpha_{ips}I_{ps} - TP} \geq 0 \tag{9}$$

Equation (1), represents the objective function addressing minimization of associated total costs to energy consumption, reconfiguration, machines idle time and maximization of potential profit of responding to increased demand.

Equation (2), guaranties the unique reconfiguration system is selected for each season. Equation (3) determines layout configuration i in season s is changed to layout configuration j in next season. Equation (4) guarantees that production volume by each process routing does not exceed its maximum capacity. Equation (5) determines number of products p processed by each process routing in the selected system configuration for each period. Equation (6) calculates total energy consumption cost of the system during working time. Equation (7) computes total idle cost including fixed idle cost throughout the time and total energy consumption cost during idle time. Equation (8) calculates total reconfiguration system cost between seasons. Equation (9) calculates scalability of the system. In fact, degree of the system scalability is optimized through maximizing the profit of the system by increasing the system utilization up to 100% to meet the potential increased demand.

3.3. The final model (MILTEC) [57]

A comprehensive linear mixed integer mathematical model is finally proposed to minimize the total energy consumption cost (MILTEC), the total transportation cost of work-in-process between machines, and the total reconfiguration cost, depending on fluctuations in energy pricing and demand during the time simultaneously.

Various demands of different products which are known should be satisfied by corresponding configurations of the manufacturing system according to demand fluctuation during periods of the time planning horizon and changing energy price between and within periods. System configuration planning consists of machine configuration and task sequencing which incorporate several design features including task scheduling, alternate process routings, the completion time for each product, and machines configuration including purchasing machines, duplicate machines, and machines arrangement at each period over the planning horizon. It is assumed that the same number of tasks should be done for each type of product for purpose of mathematical simplicity.

The manufacturing strategy is a batch production. The batch size represents the product demand. The batch of each task should be done by just one machine without any interruption with aim of simplification. The system consists of a given number of machines that have to be set in the layout with a given number of locations as shown in Figure 5.

1	2	3
4	5	6

Figure 5- Layout

There is a set of alternative machines to process each task with some negative or positive impacts on the energy consumption and the processing time which are all known. It means different machines consume different amounts of time and energy to do the same task. It improves flexibility through providing alternative process routings which help to assign tasks to machines in an effective way and obtain a better system configuration planning.

There is no particular direction of material handling in the system to transport parts from one machine to another. Parts are transported between machines based on travel distance matrix presented in Figure 6. Material handling cost per unit of distance for all products are known. Using duplicate machines in the layout can improve the system performance.

	1	**2**	**3**	**4**	**5**	**6**
1	0	1	2	1	2	3
2	1	0	1	2	1	2
3	2	1	0	3	2	1
4	1	1	3	0	1	2
5	2	1	2	1	0	1
6	3	2	1	2	1	0

Figure 6- Travel Distance Matrix

The reconfiguration cost of each machine type between two periods of time is given. It is assumed that the installing and uninstalling cost are the same. Both installing and uninstalling are required for each machine reconfiguration between two periods of time while installing cost is just needed for adding the new machine besides of purchasing cost which is also known.

Any task can start processing when its predecessors are done. The idle cost is considered negligible. In this model, it is assumed that all machines have a same limited capacity to process tasks expressed in a maximum number of tasks can be operated on one machine during a period of time. A task priority counter on each machine is defined which cannot be more than the limited capacity of machines. It just helps to prioritize assigned tasks on each machine to calculate completion time of each task.

According to the survey of TOU electricity pricing programs targeting industrial customers in the U.S conducted by Wang and Li, time and price of on-, mid-, off- peak periods of electricity are varying in each state. The energy consumption cost is considered based on the daily TOU energy pricing which is repeated throughout a period as shown in Figure 7.

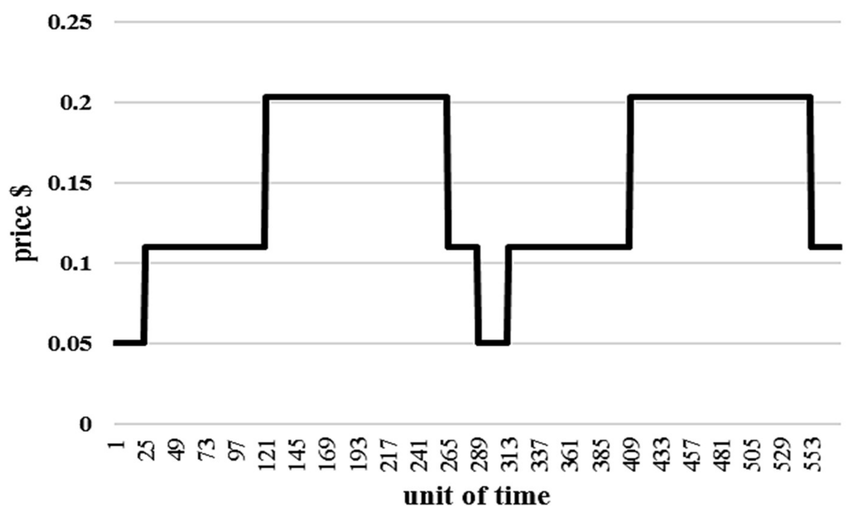

Figure 7- Energy Pricing

Time periods could be defined by weeks, months, or seasons. For instance, if a time period is assumed as a month, a particular daily TOU electricity pricing program is repeated for 30 days in which the energy price is stable during a couple of hours but different between on-, mid-, off- peak periods in every day. It means energy price can be different within time intervals depends on the time during which task is done in a day. Fluctuation in energy pricing between periods is also assumed in this model. Maximum working hours in a day is 12 hours. It is assumed that the unit of time is 2.5 minutes which means 288 units of time is equal to 12 hours. All parameters are constant and known in prior.

The presented model (MILTEC) minimizes the total energy consumption cost, the total transportation cost of work-in-process between machines, and the total reconfiguration cost, depending on fluctuations in energy pricing and demand during the time which has not been considered simultaneously before. According to the changing energy price within and between periods, the MILTEC model determines the exact time during which each task is performed from start to completion of process in order to precisely calculate its energy consumption cost based on its associated energy price on a particular time in a day. This is a main part of novelty in this mathematical model to calculate energy consumption cost of each task based on the exact time during which is performed. The following notations are used in the MILTEC model.

Nomenclature

m, m'	Type of Machine, m= 1,2, …, M, where M is the number of machines
l, l'	Location, l=1,2, …, L, where L is the number of locations in the layout
T	Time Period, t=1, 2, …, T, where T is the horizon time
p, p'	Product, p=1, 2, …, P, where P is the number of products
r, r'	Tasks, r=1, 2, …, R, where R is the number of tasks to produce a product
b, b'	task priority counter on machines, b=1, 2, …, B, where B is the maximum number of tasks can be operated on one machine during a period of time
h, h'	Changing time, h=1, 2, …, H, where H is the number of times that energy price is changed in each period

Parameters

V_{mrp}	Equal to 1 when the machine m can operate the task r of product p
PT_{mrp}	Processing time for task r of product p on the machine m
E_{mrp}	Energy consumption of machine m when operates task r of product p

D_{pt} Demand of product p in the period t

$DI_{ll'}$ Distance between location l and l' in the layout

TOU_h A time duration that energy has a particular stable price.

EP_{ht} Energy price in time h and period t

MH_p Material handling cost for a unit of product p per unit of distance

γ_m Purchasing cost of machine m

φ_m Reconfiguration cost of machine m

$W_{1,2,3}$ Different weights of reconfiguration, energy, and material handling terms in the objective function

Decision variables

y_{mlt} Binary variable, equal to 1 when machine m is in location l in period t

w^{+}_{mt} Number of added machine m in period t

w_{mlt} Binary variable, equal to 1 when machine is swapped with another machine at location l in period t

x^{rpb}_{mlt} Binary variable, when task r of product p is done by machine m at location l in priority b in period t

c^{rpb}_{mlt} Completion time of task r of product p that is done by machine m at location l in priority b in period t

s^{rpb}_{mlt} Starting time of task r of product p that is done by machine m at location l in turn b in period t

ec^{rpbh}_{mlt} Energy consumption cost of task r of product p by machine m is in location l in time h of period t

$u^{rp}_{mlm'l't}$ Binary variable, equal to 1 when product p should be transported from machine m in location l to machine m' in location l'

Auxiliary variables

hc_{mlt}^{rpbh} Positive Auxiliary variable which is dependent on completion time to calculate the energy cost

hs_{mlt}^{rpbh} Positive Auxiliary variable which is dependent to starting time to calculate the energy cost

α_{mlt}^{rpbh} Binary Auxiliary variable, equal to 1 from beginning of a day to starting time of task r of product p that is done by machine m at location l in turn b in period t

α'^{rpbh}_{mlt} Binary Auxiliary variable, equal to 1 from beginning of a day to completion time of completion time of task r of product p that is done by machine m at location l in turn b in period t

<u>Objective</u>

Minimize

$$W_1\left(\ \tfrac{1}{2}\sum_m\sum_t(w_{mt}^{+})\,.\,\varphi_m + \sum_m\sum_t w_{mt}^{+}\,.\,\gamma_m + \sum_m\sum_l\sum_t w_{mlt}\,.\,\varphi_m\right) \tag{1-1}$$

$$+\ W_2\left(\ \sum_m\sum_l\sum_t\sum_r\sum_p\sum_b\sum_h ec_{mlt}^{rpbh}\right) \tag{1-2}$$

$$+\ W_3\left(\ \sum_m\sum_l\sum_{m'}\sum_{l'}\sum_t\sum_r\sum_p u_{mlm'l't}^{rp}\,.\,MH_p\,.\,DI_{ll'}\right) \tag{1-3}$$

S.T.

Part(A): tasks scheduling and Machine Allocation

$$x_{mlt}^{rpb} \le V_{mrp} \qquad \forall\, m\in M;\ l\in L;\ t\in T;\ r\in R;\ p\in P;\ b\in B \tag{2}$$

$$x_{mlt}^{rpb} - y_{mlt} \le\ 0 \qquad \forall\, m\in M;\ l\in L;\ t\in T;\ r\in R;\ p\in P;\ b\in B \tag{3}$$

$$\sum_r\sum_p\sum_b x_{mlt}^{rpb} - y_{mlt} \ge\ 0 \qquad \forall\, m\in M;\ l\in L;\ t\in T \tag{4}$$

$$\sum_m y_{mlt} \le 1 \qquad \forall\, l\in L; t\in T \tag{5}$$

$$\sum_m\sum_l y_{mlt} \le L \qquad \forall\, t\in T \tag{6}$$

$$M.\sum_m \sum_l \sum_b x_{mlt}^{rpb} \geq D_{pt} \qquad \forall t \in T;\ r \in R;\ p \in P \tag{7}$$

$$\sum_m \sum_l \sum_b x_{mlt}^{rpb} \leq D_{pt} \qquad \forall t \in T;\ r \in R;\ p \in P \tag{8}$$

$$\sum_m \sum_l \sum_b x_{mlt}^{rpb} \leq 1 \qquad \forall t \in T;\ r \in R;\ p \in P \tag{9}$$

$$\sum_r \sum_p x_{mlt}^{rpb} \leq 1 \qquad \forall\, m \in M;\ l \in L;\ t \in T;\ b \in B \tag{10}$$

Part B: Completion Time

$$s_{mlt}^{rpb} - c_{mlt}^{r'p'b'} + M.\left(2 - x_{mlt}^{rpb} - x_{mlt}^{r'p'b'}\right) \geq 0 \qquad \forall\, m \in M;\ l \in L;\ t \in T;\ r, r' \in R;\ p, p' \in P;\ b, b' \in B\ |b > b' \tag{11}$$

$$s_{mlt}^{rpb} - c_{m'l't}^{r'pb'} + M.\left(2 - x_{mlt}^{rpb} - x_{m'l't}^{r+1,pb'}\right) \geq 0 \qquad \forall\, m, m' \in M;\ l, l' \in L;\ t \in T;\ r \in R;\ p \in P;\ b, b' \in B \tag{12}$$

$$c_{mlt}^{rpb} - s_{mlt}^{rpb} + M.\left(1 - x_{mlt}^{rpb}\right) \geq D_{pt}.PT_{mrp} \qquad \forall\, m \in M;\ l \in L;\ t \in T;\ r \in R;\ p \in P;\ b \in B \tag{13}$$

$$c_{mlt}^{rpb} - s_{mlt}^{rpb} - M.\left(1 - x_{mlt}^{rpb}\right) \leq D_{pt}.PT_{mrp} \qquad \forall\, m \in M;\ l \in L;\ t \in T;\ r \in R;\ p \in P;\ b \in B \tag{14}$$

Part C: Energy Cost

$$s_{mlt}^{rpb} - \sum_h hs_{mlt}^{rpbh} = 0 \qquad \forall\, m \in M;\ l \in L;\ t \in T; r \in R;\ p \in P;\ b \in B \tag{15}$$

$$c_{mlt}^{rpb} - \sum_h hc_{mlt}^{rpbh} = 0 \qquad \forall\, m \in M;\ l \in L;\ t \in T; r \in R;\ p \in P;\ b \in B \tag{16}$$

$hs_{mlt}^{rpb,1} \leq TOU_1$ $\quad \forall\, m \in M;\ l \in L;\ t \in T; r \in R;\ p \in P;\ b \in B$ (17)

$hs_{mlt}^{rpbh} - TOU_h . \alpha_{mlt}^{rpbh-1} \leq 0$ $\quad \forall\, m \in M;\ l \in L;\ t \in T;\ r \in R;\ p \in P;\ b \in B; h \in H|\ h > 1$ (18)

$hs_{mlt}^{rpbh} - TOU_h . \alpha_{mlt}^{rpbh} \geq 0$ $\quad \forall\, m \in M;\ l \in L;\ t \in T;\ r \in R;\ p \in P;\ b \in B; h \in H|\ 1 < h < H$ (19)

$hc_{mlt}^{rpb,1} \leq TOU_1$ $\quad \forall\, m \in M;\ l \in L;\ t \in T;\ r \in R;\ p \in P;\ b \in B$ (20)

$hc_{mlt}^{rpbh} - TOU_h . {\alpha'}_{mlt}^{rpbh-1} \leq 0$ $\quad \forall\, m \in M;\ l \in L;\ t \in T;\ r \in R;\ p \in P;\ b \in B; h \in H|\ h > 1$ (21)

$hc_{mlt}^{rpbh} - TOU_h . {\alpha'}_{mlt}^{rpbh} \geq 0$ $\quad \forall\, m \in M;\ l \in L;\ t \in T;\ r \in R;\ p \in P;\ b \in B; h \in H|\ 1 < h < H$ (22)

$\alpha_{mlt}^{rpbh\prime} - \alpha_{mlt}^{rpbh} \geq 0$ $\quad \forall\, m \in M;\ l \in L;\ t \in T;\ r \in R;\ p \in P;\ b \in B; h, h' \in H|\ h' < h$ (23)

${\alpha'}_{mlt}^{rpbh\prime} - {\alpha'}_{mlt}^{rpbh} \geq 0$ $\quad \forall\, m \in M;\ l \in L;\ t \in T;\ r \in R;\ p \in P;\ b \in B; h, h' \in H|\ h' < h$ (24)

$(hc_{mlt}^{rpbh} - hs_{mlt}^{rpbh}) . EP_{ht} . E_{mrp} - ec_{mlt}^{rpbh} \leq 0$ $\quad \forall\, m \in M;\ l \in L;\ t \in T;\ r \in R;\ p \in P;\ b \in B; h \in H$ (25)

Part D: Reconfiguration Cost

$\sum_l y_{ml,1} - w_{m,1}^{+} = 0$ $\quad \forall\, m \in M$ (26)

$\sum_l y_{mlt} - \sum_l y_{ml,t-1} - w_{mt}^{+} \leq 0$ $\quad \forall\, m \in M; t \in T \mid t > 1$ (27)

$y_{mlt-1} - y_{ml,t} - w_{mlt} \leq 0$ $\quad \forall\, m \in M;\ l \in L;\ t \in T$ (28)

Part E: Material Handling Cost

$x_{mlt}^{rpb} + x_{m'l't}^{r+1,pb'} - 1 - u_{mlm'l't}^{rp} \leq 0$ $\quad \forall\, m, m' \in M;\ l, l' \in L;\ t \in T;\ r \in R | r < R;\ p \in P;\ b, b' \in B$ (29)

Equation (1), represents the objective function addressing minimization of associated cost to layout reconfiguration, energy consumption, and material handling. Since the objective functions have a different scale but same nature, a weighted function is proposed. In addition, all terms of objective are representing cost though, different weight can be applied to these terms according to different priorities on the objectives. For example, greater weight can be applied to energy consumption cost due to environmental concern along with economic aspect. Term (1-1) is the reconfiguration cost including purchasing, installing a new machine, and replacing two existing machines between two locations. It is assumed that the installing and uninstalling cost are the same. Both installing and uninstalling are required for each machine reconfiguration while the installing cost is just needed for adding the new machine. Term (1-2) is the energy consumption cost. Term (1-3) is the material handling cost of work-in-process between machines.

Part A including constraints 2 to 10 allocates a number of machines to different locations of the layout and schedules tasks between machines. Constraint 2 guarantees that each process should be assigned to one of its alternative machines set. Constraint

3 guarantees that tasks are assigned to allocated machines in the layout. Constraint 4 guarantees that each machine in the layout processes at least one task during a time period. Constraint 5 guarantees that each location of the layout should be assigned to just one machine during a time period. Constraints 6 ensures the number of all machines in the layout should not be more than the number of locations. Constraints 7 to 10 guarantee that each process should be done just by one machine at the particular location in a specific time of each period time. Constraints 8 and 9 are both necessary because if there is no demand for a particular product in a period of time, the product should not be assigned to any machines during that time. On the contrary, if there is a demand for a product, all related tasks should be done by one machine at the particular location in the same time period.

Part B including constraints 11 to 14 calculates completion time of all tasks. Constraint 11 guarantees that starting time of a task should be at least equal to the completion time of another task which is done before by the same machine at the same location. Constraint 12 guarantees that starting time of a task should be at least equal to the completion time of its predecessor by any machine at any location. Constraints 13 to 14 calculates completion time of all tasks.

Part C including constraints 15 to 25 calculate the energy consumption cost of each machine in the system. Constraints 15 to 24 determine the time between start and completion of each task processing to determine the energy price of corresponding time. Constraint 25 calculates the energy consumption cost. Part D including constraints 26 to 28 help to calculate the reconfiguration cost in the objective. Constraints 26 to 27 determine added machines to the system in each time period. Constraint 28 determines machines that are relocated in the layout compared to last period. Part E including constraint 29 help to calculate the material handling cost. It determines each two locations in which two consecutive tasks of a particular product are transported.

CHAPTER 4

Case Studies

4.1. The basic model (MSCM) [54]

To demonstrate the efficiency of the proposed model, 9 numerical examples are considered. These examples include combination of three different number of machines and jobs. Basic characteristics of these problems are indicated in table 2. It should be noticed that energy consumption of jobs is distributed uniformly in the range of 5 to 12 kWh per machines. Transportation cost of jobs and setup cost of machines for each job are uniformly generated respectively in the range of 35 to 45 and 25 to 40 U.S. dollars per hour. In addition, working time is supposed to be 12 hours in a day and time unit (TU) is assumed to be 10 minutes. For instance, the period of 8 A.M to 11 A.M is defined as 18 time units.

Regarding the survey of TOU electricity pricing in the U.S conducted by Wang and Li, time and price of on-, mid-, off- peak periods of electricity are varies in each state [13]. In this research, it is assumed that manufacturing system is in AZ state as one of most expensive electricity pricing zones of U.S [13]. Based on the survey, the TOU pattern of electricity pricing in AZ State has four periods for 12 hours (from 8 A.M to 8 P.M): 1) the period of 8 to 11 A.M (from 1 to 18 TU) is off-peak period. 2) The period of 11 A.M to 2 A.M (from 19 to 36 TU) is Mid-peak period. 3) The period of 2 to 7 P.M (from 37 to 65 TU) is on-peak and 4) the period of 7 to 8 P.M (from 65 to 72 TU) is again Mid-peak period. Besides, the electricity pricing of AZ state in on-, mid- and off-peak periods are 0.203, 0.11, 0.05 $ per hour [13].

Table 2. Basic Characteristics

Test Problem No.	Number of Machines	Number of Jobs	Size of Problem	Computational Time (Second)
1	5	5	25	5.51
2	5	10	50	11.97
3	10	5	50	29.33
4	15	5	75	41.97
5	5	15	100	106.18
6	10	10	100	467.16
7	15	10	150	1005.94
8	10	15	200	877.07
9	15	15	300	1014.01

Test problems are solved by GAMS software on a desktop Core i7, 3.40 GHz with 16 GB RAM. Computational time for each problem is shown in table 2. As it is expected, computational time gradually increased with problem size increasing. As it mentioned before, the model output is a system configuration plan, indicating arrangement of machines in the system, and the sequence of jobs, which is needed to be produced. For instance, in the first problem, Figure 8 shows the best arrangement of machines and, Figure 9 depicts the trend of energy consumption cost and sequence of jobs based on the TOU pattern of energy pricing in AZ state during a day. Figure 9 shows the proposed model schedules jobs with lower energy consumption throughout on-peak period in order to minimize the energy consumption cost.

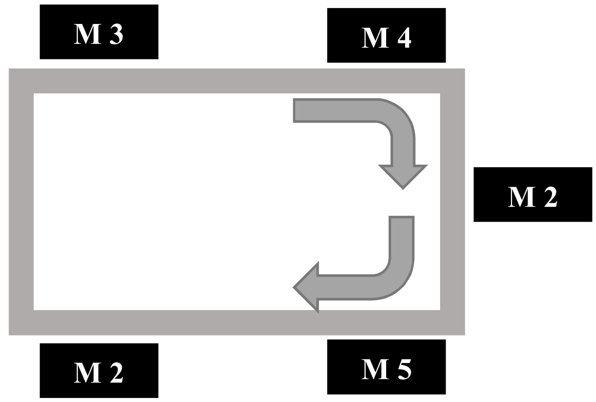

Figure 8. Best arrangement of machines

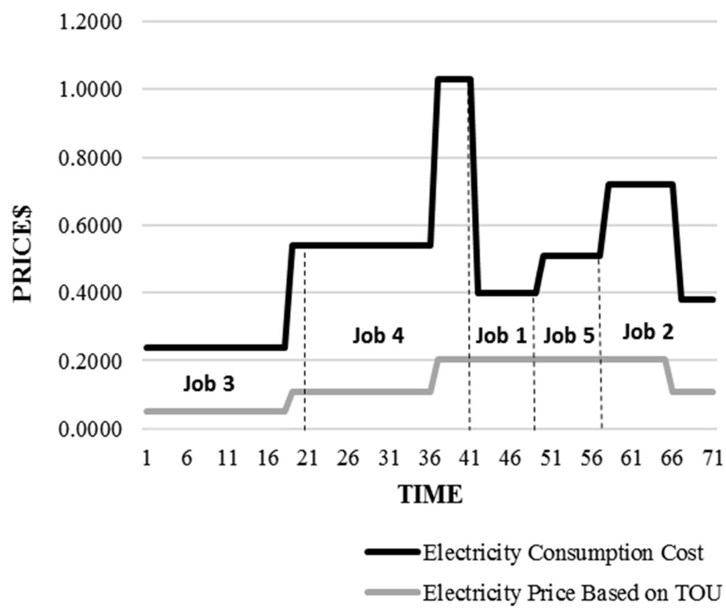

Figure 9. Electricity consumption cost based on TOU pattern

Table 3 reports objective function and three associated costs of energy consumption, sequence-dependent setup of machines and transportation of jobs in nine different test problems. It shows the efficiency and practicality of the proposed model, since it finds the optimum configuration plan and job sequence with minimum objective function in a reasonable time. Since test problems are in different sizes, all parameters are different and objective functions are not comparable.

Table 3. Objective function

Test Problem No.	SC	TEC	TC	Z
1	312.35	345.77	301.4	959.52
2	229.35	124.5	366.27	720.13
3	90.07	348.4	644.68	1083.16
4	204.28	368.3	553.58	1126.17
5	338.43	111.91	440.01	877.86
6	160.78	167.09	687.46	1015.34
7	186.68	141.86	693.07	1021.62
8	119.8	163.22	1030.12	1324.361
9	146.65	111.3	1205.1	1463.06

4.2. The second model (MSSCM) [55], [56]

To demonstrate the efficiency of the proposed model, 9 numerical examples are considered. These examples include combination of three different numbers of potential layout configurations and time periods which is shown in table 4 sorted in size.

Table 4-Test problems characteristics

Test problem number	1	2	3	4	5	6	7	8	9
No. of layout configuration alternatives	5	5	5	20	20	50	20	50	50
No. of time periods	4	6	12	4	6	4	12	6	12

Number of products and process routings are assumed 10 and 3 respectively. The average energy price in seasonal, two months, and monthly terms are shown in tables 5, 6, 7 respectively. There is a deviation between [-10% +10%] from the average energy price for each layout configuration.

Table 5-Seasonal average energy price

Seasonal	Winter	Spring	Summer	Fall
$/MWH	77.3	70.6	72.8	66.8

Table 6-Two months' average energy price

Two-Months	Jan-Feb	Mar- Apr	May-Jun	Jul-Aug	Sep-Oct	Nov-Dec
$/MWH	110.5	103	121.5	144	118	84

Table 7-Monthly average energy price

Monthly	Jan	Feb	Mar	Apr	May	Jun
$/MWH	109	112	87	119	116	127
Monthly	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
$/MWH	148	140	120	116	84	84

It should be noticed that energy consumption of alternative process routings is distributed uniformly in the range of 0.1 to 0.5 Megawatt hour (MWh) to produce one unit of part p. Test problems are solved by GAMS software on a desktop Core i7, 3.40 GHz with 16 GB RAM. Computational time for each problem is shown in table 8. As it is expected, computational time gradually increased with problem size increasing. The model output is a system configuration selection, indicating layout configuration for each period of time and production volume of products by each process routing in the system configuration selected.

Table 8-Computational time

Test problem number	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Time(Second)	14.35	45.53	120.5	440.5	849.18	1420.4	2950.4	3754.9	7853.7

Table 9 shows objective function and the four associated costs of energy consumption (TEC), layout reconfiguration (TTC), machines idle time (TIC), and potential profit of responding to increased demand (TP). Tables 8-9 proves the efficiency of the proposed model since the model finds the minimum objective function in a reasonable time. Figure 10 shows that the objective function value is increased by increasing the number of time periods, since the more system configurations are changed during the year, the more cost is generated.

Table 9- Objective Function values

Test problem No.	**Obj. Function**	**TEC**	**TTC**	**TRC**	**TIC**	**TP**
1	25,108.4	1,616.5	11,499	2,403	7,223	6,090.8
2	50,277.5	3,269.8	19,181	3,565	6,485	5,826.1
3	116,540.5	6,863.2	41,723	10,473	7,820	6,054.1
4	21,981.9	1,402.5	9,559	2,525	5,748	4,938.0
5	45,093.3	3,115.2	16,732	4,067	6,885	6,871.3
6	109,985.1	6,690.0	39,709	8,801	6,801	6,112.9
7	23,441.2	1,387.5	9,653	2,789	11,234	14,119.2
8	45,352	2,936.2	17,410	4,464	6,068	5,976.1
9	116,864	6,666.0	46,532	9,632	6,217	6,088.5

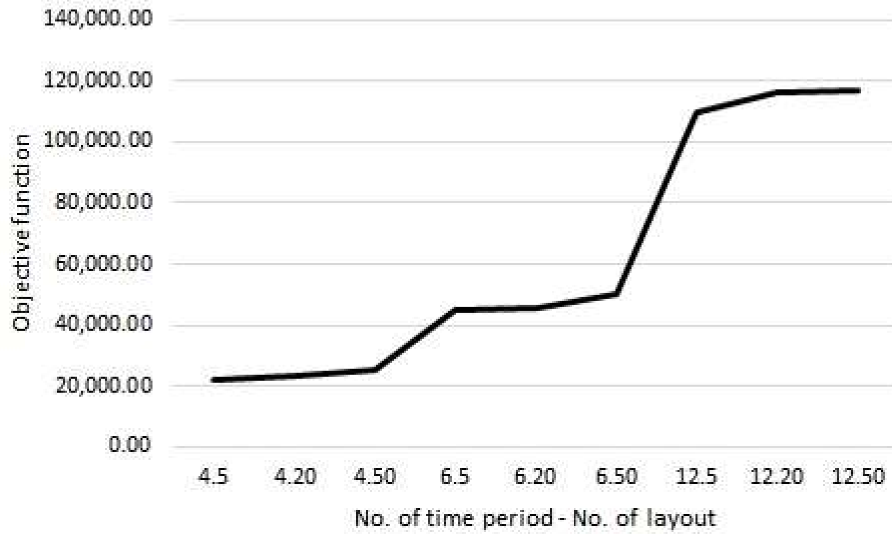

Figure 10- Objective Function Value

In order to analyze the influence of energy pricing and demand fluctuation on layout configuration and material handling selection, the model is solved for one of nine test problems several times with different demand and energy pricing. For instance, result of the model for test problem number 4 is shown in table 10. The proposed model selects layout configurations 16, 20, 17, 19 for each season respectively. The energy price is increased in three levels (two, five, and ten times).

	Time period no.	**1**	**2**	**3**	**4**
Test problem 4	layout configuration	16	20	17	19
***2**	layout configuration	19	16	17	19
***5**	layout configuration	19	16	11	19
***10**	layout configuration	19	12	11	19

Table 10- Sensitive Analysis of model by parameter C (The average energy price)

As it is shown in table 10, system reconfiguration selections are changed, since the system convertibility and reconfiguration selection is sensitive to volatile energy pricing. The important reason is that system energy consumption is dependent on the selected layout configuration and material handling system during each season.

Scalability is about the degree of response to demand fluctuation by changing the production rate. In this paper, probability of particular percentage of change in demand is considered as a demand fluctuation index to analyze the influence of demand fluctuation on system reconfiguration selection. For instance, high probability means high demand change. Test problem number 4 is solved with three different probability of change in demand (half, two, and five time). System reconfiguration selection is affected by changing the probability of change in demand as it is shown in table 11, since the proposed model tries to maximize the system scalability by changing the configuration of layout to respond to changed demand

Table 11 - Sensitive Analysis of model by parameter α

	Time period no.	**1**	**2**	**3**	**4**
test problem 4	layout configuration	16	20	17	19
***2**	layout configuration	19	20	17	19
***5**	layout configuration	19	20	14	10
***0.5**	layout configuration	16	17	20	13

4.3. **The final model (MILTEC)** [57]

To demonstrate the efficiency of the proposed model, 6 numerical examples in small scale are considered. All examples are tested 7 times by applying different weights of objective function terms to analyze the model sensitivity by GAMS software through using the branch and bound algorithm. Basic characteristics of these problems are indicated in table 12. A number of products, time periods and, required tasks of each product are assumed to be respectively 2, 4 and, 2. It should be noticed that all parameter are generated uniformly for each example. Energy consumption of tasks is distributed uniformly in the range of 5 to 12 kWh per machine. Reconfiguration, purchasing and, material handling costs are uniformly generated respectively in the range of 100 to 300 U.S. dollar per machine, 1000 to 1700 U.S. dollar per machine and 3 to 15 U.S. dollar per unit of distance. Demand is also uniformly generated in the range of 0 to 300. Working time is supposed to be 12 hours in a day and time unit (TU) is assumed to be 2.5 minutes. For instance, the period of 8 A.M to 9 A.M is defined as 24 time units. As TOU pattern of energy pricing program in AZ state as one of most expensive electricity pricing zones of U.S referring to the survey of TOU electricity pricing programs targeting industrial customers in the U.S conducted by Wang and Li, it is assumed that there are four parts for 12 hours (from 8 A.M to 8 P.M/ 288 TU): 1) The part of 8 to 9 A.M (24 TU) is off-peak period. 2) The part of 9 A.M to 1 P.M (96 TU) is Mid-peak period. 3) The part of 1 to 7 P.M (144 TU) is on-peak and 4) the part of 7 to 8 P.M (24 TU) is again Mid-peak period. In addition, the electricity pricing of AZ state in on-, mid- and off-peak periods are 0.203, 0.11, 0.05 $ per kilowatt-hour[46]. Therefore, energy pricing is changed 4 times in a day by [0.5 1.5] $. A time period consists of several days (a week, a month, a season). For instance, if h is 28, where is the number of times that energy price is changed in each time period, it means each period of time consists of 7 days. Energy pricing during 4 periods of two days (h=8) is shown in table 14. It should be noticed that the periodical (seasonal) energy pricing changes are generalized based on the paper assumption which is between [0.1 0.4] $.

Table 12-Problem Dimension

test problem No.	No. of Machines (m)	No. of Locations (L)	No. of Time Unit (h)
p1	2	2	8
p2	2	2	16
p3	2	3	8
p4	2	3	16
p5	3	4	24
p6	3	4	32

Table 13- Energy Pricing (EP_{ht}) of 4 time periods

period / h	1	2	3	4
1	0.05	0.04	0.06	0.03
2	0.11	0.9	0.12	0.1
3	0.203	0.2	0.21	0.201
4	0.11	0.9	0.12	0.1
5	0.05	0.04	0.06	0.03
6	0.11	0.9	0.12	0.1
7	0.203	0.2	0.21	0.201
8	0.11	0.9	0.12	0.1

Test problems are solved by GAMS software on a desktop Core i7, 3.40 GHz with 16 GB RAM. As mentioned before, the model output is a system configuration plan, indicating the arrangement of machines in the system, and the sequence of tasks. It is found that sequence of tasks is mostly changed in all test problems throughout the time since energy pricing, product portfolio and demand is varying. Figure 11 shows tasks sequencing and energy consumption trend of test problem 3 in the first period of time based on the energy pricing pattern as an example. It depicts that the proposed model schedules tasks with lower energy consumption during the on-peak period to minimize the energy consumption cost.

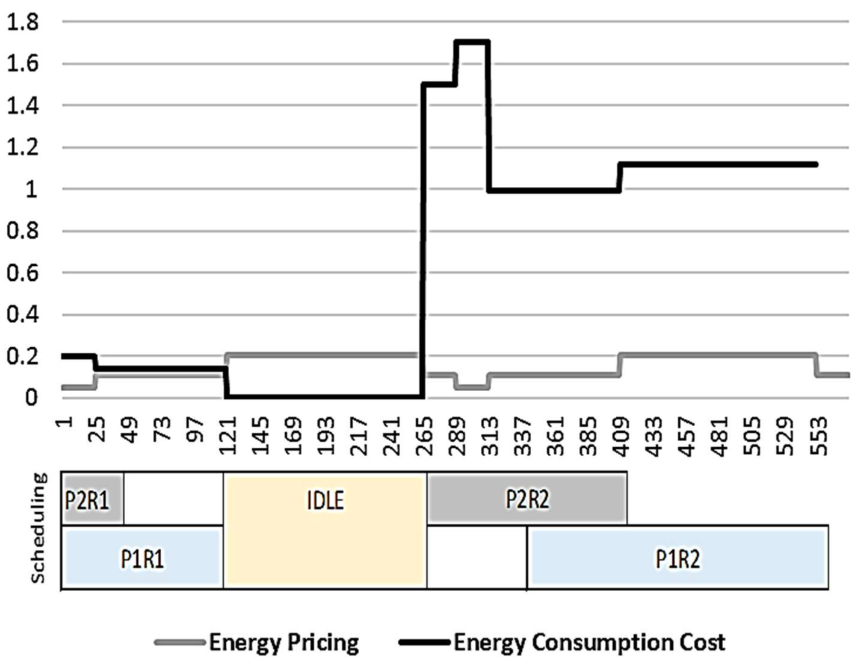

Figure 12- Energy Consumption & Job Scheduling e.g. P1R2 = process number 2 of product

The layout configuration of all test problems in each period of time among applied different weights of reconfiguration, energy, and material handling terms in the objective function are represented in Figure 12. It shows that system reconfiguration in a longer period of time (higher value of h) is more desirable since short-term reconfiguration may not have economical benefits. For instance, there are more reconfigurations (yellow spots) in problems 5 and 6 compared to other problems shown in Figure 12. Problems are tested 7 times by applying different weights of objective function terms to analyze the model sensitivity to reconfiguration costs, changing energy pricing and demand. As it is expected, reconfiguration cost plays an important role in reconfiguration decision making, specifically in the short-term periods. According to changing the weight of reconfiguration cost to 10, it is found that short-term layout reconfiguration is not economic efficient. It is also found that unstable energy pricing can greatly affect the system reconfiguration plan in order to minimize the cost. Due to applying weights of [1, 10, 1] to reconfiguration, energy, and material handling costs in the objective function, Figure 11 shows that changing energy pricing forces the system to have layout reconfiguration to minimize the energy consumption cost. The effect of varying demand on the system reconfiguration plan is also analyzed by applying weights of [1, 1, 10] respectively to reconfiguration, energy, and material handling terms in the objective function. It shows varying demand also affects the system reconfiguration to minimize the material handling cost. When both weights of energy and material handling terms are changed to 10 simultaneously, the system is again forced to have a layout reconfiguration. As these three mentioned columns representing weights of [1, 10, 1], [1, 1, 10], and [1, 10, 10] consist of larger number of reconfigurations (larger number of yellow spots) compared to other columns shown in Figure 12, it is concluded that unstable energy pricing and demand fluctuation influence on even the short-term reconfiguration plan.

Problem No.	Location (L)	Weights of Obj.F. w= [1 1 1]				Weights of Obj.F. w= [10 1 1]				Weights of Obj.F. w= [1 10 1]				Weights of Obj.F. w= [1 1 10]				Weights of Obj.F. w= [10 10 1]				Weights of Obj.F. w= [10 1 10]				Weights of Obj.F. w= [1 10 10]			
		Time periods (t)				Time periods (t)				Time periods (t)				Time periods (t)				Time periods (t)				Time periods (t)				Time periods (t)			
		t=1	t=2	t=3	t=4	t=1	t=2	t=3	t=4	t=1	t=2	t=3	t=4	t=1	t=2	t=3	t=4	t=1	t=2	t=3	t=4	t=1	t=2	t=3	t=4	t=1	t=2	t=3	t=4
p1	L1	M1	M1	M1		M2	M2	M2	M2	M2	M2	M2	M2	M2	M2	M2	M2	M1	M1	M1		M2	M2	M2	M2	M2	M2	M2	M2
	L2	M2	M2	M2	M2	M1	M1	M1	M1	M1	M1	M1		M1	M1	M1		M2	M2	M2	M2	M1	M1	M1		M1	M1	M1	
p2	L1	M1	M1	M1	M1	M1	M1	M1	M1	M1	M1	M1	M1		M2		M2		M2	M2	M2	M1	M1	M1	M1		M2	M1	M1
	L2		M2	M2	M2	M2	M2	M2	M2		M2	M2	M2	M1	M1	M1	M1	M1	M1	M1	M1		M2	M2	M2	M1			M2
p3	L1	M2	M2	M2	M2									M2				M2	M2	M2	M2	M2	M2	M2	M2	M1	M1	M1	
	L2	M1	M1	M1		M2	M2	M2	M2	M1	M1	M1		M1	M1	M1						M1	M1	M1	M1				
	L3					M1	M1	M1	M1	M2	M2	M2	M2			M2	M2	M1	M1	M1	M1					M2		M2	M2
p4	L1					M1	M1	M1	M1	M1	M1	M1		M1	M1	M1		M2	M2	M2	M2	M2	M2	M2	M2	M1	M1	M1	
	L2	M2	M2	M2	M2	M2	M2	M2	M2	M2	M2	M2	M2					M1	M1	M1	M1	M1	M1	M1				M2	M2
	L3	M1	M1	M1										M2		M2	M2									M2			
p5	L1	M1	M1	M1	M1	M2	M2	M2	M2										M3			M1	M1	M1	M3	M1	M1	M1	M1
	L2	M2	M2	M2	M3	M1	M1	M1	M3	M1	M1	M1	M1	M1	M1	M1	M1	M2	M2	M2	M2	M2	M2	M2	M2	M2	M2	M2	M3
	L3		M3							M2	M2	M2	M3	M2	M2	M2	M3	M1	M1	M1	M3			M3			M3		
	L4										M3				M3														
p6	L1					M1	M1	M1	M3		M2	M2	M3		M3				M3				M3						
	L2	M2	M2	M2		M2	M2	M2	M2			M1	M1	M1	M1	M1	M1	M1	M1	M1	M1	M1	M1	M1	M3	M1	M1	M1	M1
	L3	M1	M1	M1	M1		M3			M2	M3			M2	M2	M2					M3	M2	M2	M2	M2		M3		
	L4		M3		M3					M1	M1						M3	M2	M2	M2						M2	M2	M2	M3

Figure 13- Layout Configuration – small size
(W= [a b c] where **a** is the weight of reconfiguration term, **b** is the weight of energy term, and **c** is the weights of material handling term. **Yellow spot** represents layout reconfiguration between two consecutive time periods, **Grey spot** represents an assigned machine (M1, M2, M3) to a location (L1, L2, L3, L4), **white spot** represents empty location in the layout.)

Table 14 shows objective function values (OFV) and computational time (CT) of each run. It indicates the model in small size is solved in a reasonable time.

Table 14- OFV and CT

	w= [1 1 1]		w= [10 1 1]		w= [1 10 1]		w= [1 1 10]		w= [10 10 1]		w= [10 1 10]		w= [1 10 10]	
	OFV	**CT**	**OFV**	**CT**	**OFV**	**CT**	**OFV**	**CT**	**OFV**	**CT**	**OFV**	**CT**	**OFV**	**CT**
P1	6,320.0	12.3	37,149.5	13.21	20,305.9	16.46	8,972.0	17.2	51,135.4	14.9	49,214.0	15.62	23,771.7	14.54
P2	7,539.8	234.6	38,369.3	22.82	28,841.0	387.3	9,751.8	104.18	59,843.3	89.9	54,096.8	332.8	31,448.4	295.5
P3	4,969.6	149.5	28,741.1	16.6	16,405.4	40.9	5,362.0	47.56	40,985.3	19.46	37,899.2	191	16,865.3	38.36
P4	5,987.5	669.7	29,970.8	67.01	24,334.9	492.96	6,265.2	164.8	49,964.1	348.5	41,528.5	558.5	25,028.0	834.4
P5	4,511.0	1,776	34,156.4	41.94	11,800.7	398.7	7,586.3	7,200	41,735.4	476.4	37,752.2	683.4	14,717.4	7,212
P6	7,182.3	4,326.2	37,766.2	151.1	34,680.2	7212	14,375.3	7,212.5	65,407.4	1,787.3	44,325.3	5,198	42,303.6	7,204

Since the computational time is greatly increased by increasing the problem size shown in Figure 13 indicating it is an NP- hard class of combinatorial problem, the genetic algorithm (GA) is employed to solve the problem in larger sizes and find optimal or near optimal solutions.

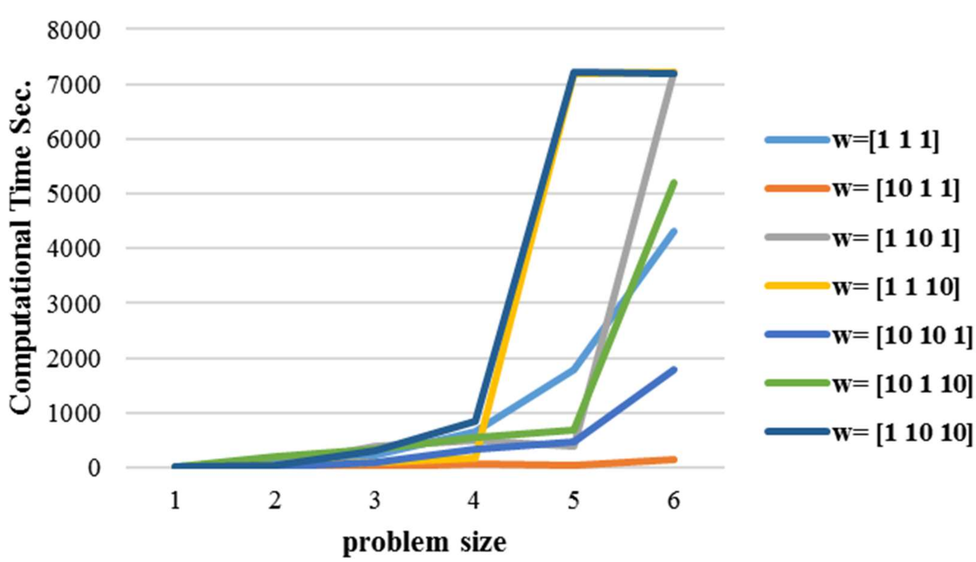

Figure 14- Computational Time Vs. Problem Size

CHAPTER 5

Meta-heuristic Algorithm

5.1. Genetic Algorithm

Genetic algorithm (GA), firstly proposed by Holland (1975), is a population-based heuristic method which employs an evolutionary pattern to find the global optimum solution. It continuously updates the population of individual solutions toward a better solution comparing current and new individuals until the stopping criterion is met and the best found solution is determined as the optimum.

GA is one of the potent optimization meta-heuristics in solving NP-hard class of combinatorial problems. Due to the complexity of proposed model, the genetic algorithm is utilized to solve the problem in larger sizes and find optimal/near optimal solutions in a reasonable time. Figure 14 represents coding structure of the chromosome for this problem. Each gene includes a positive number between 0 and 1. The chromosome includes *T(2L+3PR)+T* genes for machines arrangement, tasks assignment and scheduling. There are two solution generation methods in the applied GA to boost the efficiency. Therefore, *T* genes also exist at the end of chromosomes to determine whether the first solution generation method is employed or the second one. In each period of time, if its relative gene which is among last *T* genes is bigger than $w_3/\sum_{ofv=1}^{3} w_{ofv}$ (where w is the weight of objective function), the first-generation method is used.

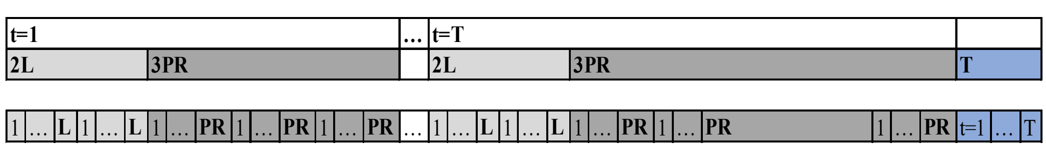

Figure 15- Coding structure of the chromosome

In the first solution generation method, all tasks of a product are assigned to a specific machine and location which means there is no material handling cost. This method is practical for cases that all tasks of each product can be done by a particular machine. Otherwise, the second method is employed to generate the solution by considering the possibility of assigning different machines to tasks of a product.

In the first method, 2L genes determine the priority of locations assignment to machines and tasks by considering the average value of each two relative gens to a location. The location with a bigger value is assigned earlier. In the second method, first L genes determine the machines set from all feasible sets to produce all products and, the second L gens determine the priority of locations assignment.

There are also *3PR* genes to assign machines to locations and schedule tasks. First PR genes prioritize tasks processing. According to what solution generation method is applied, Products or tasks are assigned to locations respectively based on the value of the relative gene. The bigger value is assigned earlier to the prioritized location. It is worth mentioning that there is a correction in the second method to ensure that each task has a bigger value than its successors which is shown in Figure 15.

0.31	0.56	0.36	0.33	0.69	0.22	0.77	0.86	0.56	0.88	0.80	0.12	0.24	0.49	0.54	0.10	0.58	0.77	0.17	0.40	0.90	0.69	0.53	0.02

0.31	0.56	0.36	0.33	0.69	0.22	0.77	0.86	0.56	0.88	0.80	0.12	0.54	0.49	0.24	0.77	0.58	0.10	0.17	0.40	0.90	0.69	0.53	0.02

Figure 16- Correction

The second PR genes select the machine from feasible alternatives to do a particular task in the assigned location. The last PR genes calculate the amount of delay to process a task. If the value of relative gene (G_{pr}) is smaller than 0.5, the task does not have any delay. Otherwise, the amount of delay is calculated by equation (30) in which TR_l represents the remained time of location l.

$$delay = max\{0, \frac{(G_{pr}-0.5)}{0.5} * (TR_l - [pt_{mrp} \times d_{pt}])\} \quad (30)$$

Three operators including crossover, mutation, and emigration are employed in this paper. A number of feasible solutions called emigrants are randomly generated and added to the population. The emigration operator helps the algorithm to escape from local optimums and find the better solution. The crossover operator selects a number of individuals from the population based on the probability crossover rate which is given. The selection is randomly conducted through one of roulette wheel or binary tournament selection methods. Three crossover operators including one-point, two-point, and weighted combination crossover are applied in this algorithm as shown in figure 16. Crossover operators have equal chances to be selected in each crossover procedure.

Three mutation operators including generation, mirror, and complementary methods are equally chanced to utilize in this algorithm. In generation method, new genes are randomly generated for the randomly selected range in the chromosome. In mirror method, selected genes are reverted. In the complementary method, each gene of the selected range is changed to 1-value as shown in figure 17.

Parents	0.95	0.84	0.56	0.43	0.19	0.99	0.89	0.83	0.40	0.77	0.99	0.76	0.88	0.23	0.48	0.55	0.28	0.34	0.08	0.43	0.95	0.88	0.50	0.48
	0.67	0.27	0.97	0.34	0.52	0.64	0.55	0.43	0.87	0.18	0.67	0.29	0.01	0.51	0.90	0.02	0.09	0.85	0.30	0.86	0.28	0.45	0.87	0.75

Children: One-point	0.95	0.84	0.56	0.43	0.19	0.99	0.89	0.83	0.40	0.77	0.99	0.76	0.88	0.23	0.48	0.02	0.09	0.85	0.30	0.86	0.28	0.45	0.87	0.75
	0.67	0.27	0.97	0.34	0.52	0.64	0.55	0.43	0.87	0.18	0.67	0.29	0.01	0.51	0.90	0.55	0.28	0.34	0.08	0.43	0.95	0.88	0.50	0.48

Children: Two-point	0.95	0.84	0.56	0.43	0.52	0.64	0.55	0.43	0.87	0.18	0.67	0.29	0.01	0.23	0.48	0.55	0.28	0.34	0.08	0.43	0.95	0.88	0.50	0.48
	0.67	0.27	0.97	0.34	0.19	0.99	0.89	0.83	0.40	0.77	0.99	0.76	0.88	0.51	0.90	0.02	0.09	0.85	0.30	0.86	0.28	0.45	0.87	0.75

Children: Weighted Combination co=0.4	0.78	0.50	0.81	0.38	0.39	0.78	0.69	0.59	0.68	0.42	0.80	0.48	0.36	0.40	0.73	0.23	0.17	0.65	0.21	0.69	0.55	0.62	0.72	0.64
	0.84	0.61	0.72	0.39	0.32	0.85	0.75	0.67	0.59	0.53	0.86	0.57	0.53	0.34	0.65	0.34	0.20	0.54	0.17	0.60	0.68	0.71	0.65	0.59

Figure 17- Crossover operators

0.29	0.65	0.84	0.36	0.17	0.09	0.60	0.69	0.82	0.75	0.42	0.50	0.06	0.45	0.57	0.53	0.93	0.72	0.71	0.37	0.65	0.05	0.49	0.20

Generation Mutation	0.29	0.65	0.84	0.36	0.17	0.09	0.60	0.69	0.82	0.75	0.42	0.50	0.06	0.45	0.57	0.70	0.10	0.15	0.33	0.62	0.60	0.91	0.49	0.20
Mirror Mutation	0.29	0.65	0.84	0.36	0.17	0.09	0.60	0.69	0.82	0.75	0.42	0.50	0.06	0.45	0.57	0.05	0.65	0.37	0.71	0.72	0.93	0.53	0.49	0.20
Complementary Mutation	0.29	0.65	0.84	0.36	0.17	0.09	0.60	0.69	0.82	0.75	0.42	0.50	0.06	0.45	0.57	0.47	0.07	0.28	0.29	0.63	0.35	0.95	0.49	0.20

Figure 18- Mutation Operators

The pseudo code of the applied GA by this paper is presented as follow:

Genetic Algorithm

Input instance *S*
Size *npop* for population;
Rate *pcr*, *pmu*, *pemg*, and *pel* for crossover, mutation, emigrants, and elitism respectively;
Number *maxit* for iterations;
Output solution *X*

---

1. Initialization
generate *npop* feasible solutions randomly and save them in *Pop*;
evaluate members of *Pop* and save them in *Z_Pop*;
2. Loop
for *it*=1 **to** *maxit* ***do***
2.1.Emigrants
generate *nemg* feasible solutions randomly;
save them in *PopEmg*;
evaluate members of *PopEmg* and save them in *Z_PopEmg*;
2.2.Merging
Pop=*Pop*+ *PopEmg*;
2.3.Crossover
select the *ncr* parents via roulette wheel operator and save them in *Parents*;
for *nc* = 1 **to** *ncr*/2 ***do***
select solutions *nc* and *nc*+*ncr*/2 *from Parents*;
if *rand*<1/3
employ one-point crossover operator and build two children;
elseif *rand*<2/3
employ two-point crossover operator and build two children;
else
employ weighted combination crossover operator and build two children;
endif
endfor
save them in *PopCr*;
evaluate members of *PopCr* and save them in *Z_PopCr*;
2.4.Mutation
for *nm*=1 **to** *nmu* ***do***
select a random solution from *Pop*;
if *rand*<1/3
employ *generation* mutation operator and build a new solution;
elseif *rand*<2/3
employ *mirror* mutation operator and build a new solution;
else
employ *complementary* mutation operator and build a new solution;
endif
endfor
save them in *PopMu*;
evaluate members of *PopMu* and save them in *Z_PopMu*;
2.5.Merging

Pop=Pop+ PopCr+PopMu;

2.6.Selection

select the best *nel* solutions in *PopMg* and Save them in *PopEl*;

select *npop-nel* solutions *from* other members randomly and save them in *PopNotEl*;

Pop=PopEl+PopNotEl;

endfor

3. Returning the best solution

Return the best solution *X* in *Pop*;

5.2. Design of Experiments for GA -Taguchi Method

There are six important parameters that control the performance of the developed GA: *npop*, *maxit*, *pcr*, *pmu*, *pel*, and *pemg*. Taguchi method is used to develop a design of experiments to minimize parameters' influences on GA performance arising from noise variables. Based on an extensive initial analysis of the algorithm, three different levels are considered for each parameter shown in table 15. Therefore, 27 experiments are proposed which are ran 5 times. According to results of Taguchi statistical method testing sensitivity of the algorithm performance to any combinations of the design factor levels, the optimum levels of parameters are shown in table 15. Results are analyzed based on their Relative Deviation Indices (*RDI)* which is the gap percentage of each result calculated based on the best and worst ones among all runs. There is a suitable level for each parameter where has a minimum mean of RDI and maximum signal to noises among 27 experiments. Signal (S) to noise (N) ratio is calculated based on equation (31) where YT_e is the average RDIs of 5 runs for experiment e and NE is the number of experiments. Therefore, the minimum mean of means and the maximum signal to noise ratios are the optimum levels of parameters as shown in Figure 18. For instance, the optimum level of npop is 2 which has the minimum mean of the average RDI and maximum signal to its noises.

$$S/N = -10 \times \log(\textstyle\sum_e YT_e / NE) \qquad (31)$$

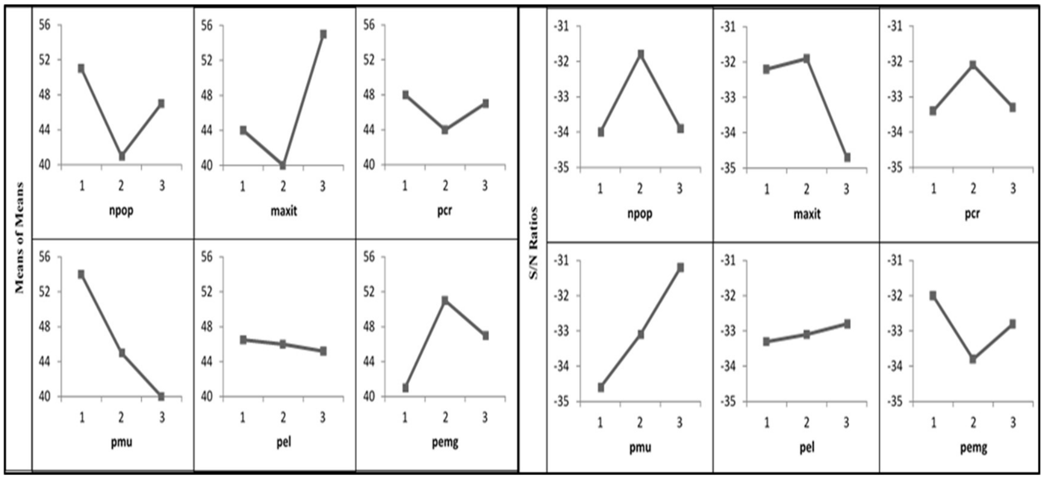

Figure 19-Taguchi results

Table 15- Parameters level

Factors	Level 1	Level 2	Level 3	Optimum Level
Npop	50	100	150	2
Maxit	100	200	300	2
Pcr	0.5	0.6	0.7	3
Pmu	0.1	0.15	0.2	2
Pel	0.5	0.7	0.9	3
Pemg	0.1	0.15	0.2	1

CHAPTER 6

Numerical examples of GA

6.1. Efficacy and Efficiency

All 6 test problems with different weights of objective function terms are solved 5 times through using GA algorithm coded in MATLAB software to evaluate the algorithm performance. Table 16 presents GA performance indexes including the best objective function value (Best OFV), the average objective function value (Av. OFV), standard deviation (STD), and the best computational time (Best Time) based on 5 times run of each test problem.

Table 16- GA Results- small size

	P1				P2			
W= [a b c]	**Best OFV**	**Av. OFV**	**STD**	**Best Time**	**Best OFV**	**Av. OFV**	**STD**	**Best Time**
[1 1 1]	6,320.00	6,325.20	4.3	14.3	7,741.90	7,747.90	3.5	13.5
[10 1 1]	37,149.50	37,166.90	26.1	16.9	39,145.30	39,168.50	25.2	13.8
[1 10 1]	20,305.90	20,346.20	55.2	15.8	29,323.70	29,653.60	250.8	13.9
[1 1 10]	9,400.00	9,409.80	6.9	12.1	10,367.60	10,377.70	8.7	11
[10 10 1]	51,135.40	51,192.70	52.6	15.7	60,897.00	61,115.20	401	15.4
[10 1 10]	49,214.00	49,217.00	3.5	14	56,132.00	56,171.40	39.5	13.2
[1 10 10]	24,400.10	24,682.00	294	12.6	32,500.40	33,113.20	480.3	12.2
	P3				**P4**			
[1 1 1]	4,969.60	4,977.00	6.1	14.3	5,981.40	6,248.30	248.6	15.8
[10 1 1]	28,748.90	29,183.80	560.6	18.6	30,046.10	30,764.20	960.2	17.4
[1 10 1]	16,405.40	16,815.90	386.7	17.5	25,244.90	25,763.00	426.2	16.9
[1 1 10]	5,562.70	5,685.90	104.3	13.4	6,325.70	6,382.10	58.5	13
[10 10 1]	41,017.70	41,487.90	546.9	17.9	50,816.00	51,686.60	995	18.4
[10 1 10]	37,899.20	37,903.40	3	15.6	40,919.40	41,374.70	414.2	15.2
[1 10 10]	17,254.10	17,939.50	452.2	13.8	25,591.70	25,982.40	336.2	14.1
			P5		**P6**			
[1 1 1]	13,535.30	13,707.90	172.2	19.9	11,910.60	12,113.40	162.1	18.6
[10 1 1]	74,971.20	76,819.10	1,408.30	19.5	73,457.80	74,093.20	698.2	18.5
[1 10 1]	58,258.50	58,959.40	804.4	19.8	44,578.60	45,444.30	923.5	18.7
[1 1 10]	28,262.80	28,518.00	285.9	19.7	24,162.30	24,687.60	364.9	18.8
[10 10 1]	120,978.50	122,686.10	1,372.50	19.8	105,934.30	108,481.60	2,190.70	18.6
[10 1 10]	89,709.60	91,008.50	1,614.60	19.9	85,579.20	86,816.40	1,562.90	18.7
[1 10 10]	72,199.80	73,899.10	1,584.40	19.6	56,652.50	57,066.40	294.1	18.8

It shows that the proposed GA find the optimum solution in a very reasonable time which proves the effectiveness of the algorithm. Coefficient Variances of results (STD/ Av. OFV) are also represented in table 17 which are negligible. It demonstrates the efficiency of the algorithm since solutions are relatively robust among running 5 times.

Table 17-The Coefficient Variance- small size

	STD/ Av. OFV					
W= [a b c]	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**
[1 1 1]	0.001	0.000	2.331	0.040	0.013	0.115
[10 1 1]	0.001	0.001	0.033	0.031	0.018	0.027
[1 10 1]	0.003	0.008	0.045	0.017	0.014	0.020
[1 1 10]	0.001	0.001	0.128	0.009	0.010	0.051
[10 10 1]	0.001	0.007	0.033	0.019	0.011	0.009
[10 1 10]	0.000	0.001	5.116	0.010	0.018	0.012
[1 10 10]	0.012	0.015	0.030	0.013	0.021	0.064

6.2. Verification

To validate the proposed GA results, the best objective function value and the computational time of each test are compared with its relative result in GAMS shown in table 18. The small gap between GA and GAMS results which is about %2.4 in average shows the algorithm finds closely the optimum solution. Results also indicate that the proposed GA greatly improves the computational time. It spends time about %70 less than GAMS in average to find the optimum solution.

Table 18- The Comparison

W= [a b c]	P1 OFV GAMS	P1 OFV GA	P1 GAP%	P1 %Time Improvement	P2 OFV GAMS	P2 OFV GA	P2 GAP%	P2 %Time Improvement
[1 1 1]	6,320.00	6,325.20	0	-16%	7,539.80	7,747.90	2.68	94%
[10 1 1]	37,149.50	37,166.90	0	-28%	38,369.30	39,168.50	2.02	40%
[1 10 1]	20,305.90	20,346.20	0	4%	28,841.00	29,653.60	1.67	96%
[1 1 10]	8,972.00	9,409.80	4.77	30%	9,751.80	10,377.70	6.31	89%
[10 10 1]	51,135.40	51,192.70	0	-5%	59,843.30	61,115.20	1.76	83%
[10 1 10]	49,214.00	49,217.00	0	10%	54,096.80	56,171.40	3.76	96%
[1 10 10]	23,771.70	24,682.00	2.64	13%	31,448.40	33,113.20	3.35	96%
	P3				**P4**			
[1 1 1]	4,969.60	4,977.00	0	90%	5,987.50	6,248.30	0.88	98%
[10 1 1]	28,741.10	29,183.80	0.03	-12%	29,970.80	30,764.20	0.02	74%
[1 10 1]	16,405.40	16,815.90	0	57%	24,334.90	25,763.00	2.2	97%
[1 1 10]	5,362.00	5,685.90	3.74	72%	6,265.20	6,382.10	2.33	92%
[10 10 1]	40,985.30	41,487.90	0.08	8%	49,964.10	51,686.60	0.63	95%
[10 1 10]	37,899.20	37,903.40	0	92%	41,528.50	41,374.70	0.03	97%
[1 10 10]	16,865.30	17,939.50	2.31	64%	25,028.00	25,982.40	3	98%
	P5				**P6**			
[1 1 1]	4,511.00	13,707.90	4.87	99%	7,182.30	12,113.40	7.7	100%
[10 1 1]	34,156.40	76,819.10	4.34	54%	37,766.20	74,093.20	2.34	88%
[1 10 1]	11,800.70	58,959.40	5.71	95%	34,680.20	45,444.30	4.47	100%
[1 1 10]	7,586.30	28,518.00	5.51	100%	14,375.30	24,687.60	3.06	100%
[10 10 1]	41,735.40	122,686.10	3.82	96%	65,407.40	108,481.60	3.95	99%
[10 1 10]	37,752.20	91,008.50	5.18	97%	44,325.30	86,816.40	7.76	100%
[1 10 10]	14,717.40	73,899.10	5.39	100%	42,303.60	57,066.40	5.25	100%

6.3. Validation

To verify the proposed GA, 6 test problems are examined in large size. All examples are tested 7 times by applying different weights of objective function terms to analyze the sensitivity of system reconfiguration (monthly, two-months, seasonal) by GA algorithm. Basic characteristics of these problems are indicated in table 19. A number of products, time periods and, required tasks of each product are assumed to be respectively 4, 4, and 3. It should be noticed that other parameters are distributed uniformly in the same range as what is mentioned before in section 3, chapter 4.

Table 19- Basic Characteristics

test problem No.	No. of Machines (m)	No. of Locations (L)	No. of Time Unit (h)
p1	5	6	112 (one month)
p2	5	6	224 (two months)
p3	5	6	336 (three months)
p4	6	8	112 (one month)
p5	6	8	224 (two months)
p6	6	8	336 (three months)

Table 20 represents GA performance indexes for large size problems. It is found that the proposed GA is also able to find the optimum solution in a very reasonable time for large size problems. Coefficient Variances of results for large size problems (STD/ Av. OFV) are also represented in table 21 which are still negligible. It verified the efficiency of the algorithm for larger sizes of the problem since there is no significant difference between solutions in several runs.

The layout configuration of all test problems in each period of time among applied different weights of reconfiguration, energy, and material handling terms in the objective function are represented in Figure 19. It shows that system reconfiguration in a longer period of time is more desirable compared to Figure 12 which is for short term reconfiguration. For instance, seasonal reconfiguration has more economically benefits than weekly reconfiguration.

Table 20-GA Results- large size

	P1				**P2**				**P3**			
W= [a b c]	**Best OFV**	**Av. OFV**	**STD**	**Best Time**	**Best OFV**	**Av. OFV**	**STD**	**Best Time**	**Best OFV**	**Av. OFV**	**STD**	**Best Time**
[1 1 1]	34,204.9	36,704.7	1,826.0	74.1	29,406.4	31,631.8	1,734.1	67.6	41,083.5	41,837.2	1,025.8	76.2
[10 1 1]	106,787.5	115,111.7	5,416.6	73.1	95,535.2	113,464.7	13,664.5	68.5	121,357.5	126,365.5	5,371.6	76.5
[1 10 1]	143,025.3	148,183.8	4,721.1	73.5	49,786.7	52,665.2	2,262.1	66.9	151,889.0	154,260.2	1,805.5	74.9
[1 1 10]	128,161.6	133,035.3	2,959.2	73.7	161,851.3	167,927.8	8,293.0	67.0	160,100.4	167,823.6	7,261.6	77.0
[10 10 1]	217,132.4	231,998.4	10,428.5	74.3	123,428.0	138,090.1	12,580.2	66.6	245,009.6	251,556.9	6,535.8	75.5
[10 1 10]	220,996.3	234,851.7	12,978.3	74.1	276,811.3	284,726.5	5,065.4	67.4	243,491.2	263,390.3	13,305.6	75.9
[1 10 10]	251,328.4	257,444.3	5,262.4	73.4	186,141.2	194,786.6	6,676.5	67.7	294,698.0	309,497.0	10,391.3	75.5

	P4				**P5**				**P6**			
W= [a b c]	**Best OFV**	**Av. OFV**	**STD**	**Best Time**	**Best OFV**	**Av. OFV**	**STD**	**Best Time**	**Best OFV**	**Av. OFV**	**STD**	**Best Time**
[1 1 1]	66,192.0	68,082.2	2,286.5	102.6	57,616.8	61,453.5	2,554.1	101.7	47,712.3	49,899.6	1,634.3	120.7
[10 1 1]	183,238.6	192,152.0	8,096.8	101.8	160,286.7	184,957.7	18,498.0	100.9	175,812.2	189,471.8	13,100.6	121.3
[1 10 1]	243,982.1	249,983.3	5,121.5	101.1	241,510.0	247,327.3	3,742.5	101.0	200,840.4	205,319.7	4,219.5	119.8
[1 1 10]	317,294.3	324,157.6	8,723.1	101.9	243,529.0	254,639.5	7,338.0	101.3	156,029.6	160,824.1	3,112.5	121.1
[10 10 1]	377,760.7	388,271.5	9,751.9	101.1	320,540.7	357,972.7	27,822.4	100.1	338,100.9	349,904.8	10,075.2	123.1
[10 1 10]	432,169.1	484,850.1	37,969.0	101.7	397,197.8	410,243.1	14,915.7	100.9	299,828.8	320,268.4	19,389.3	122.6
[1 10 10]	491,641.7	509,636.5	22,938.3	102.7	421,801.9	447,214.2	15,539.7	101.1	331,787.7	336,201.8	6,567.8	121.3

Table 21-The Coefficient Variance- large size

	STD/ Av. OFV					
W= [a b c]	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**
[1 1 1]	0.050	0.055	0.025	0.034	0.042	0.033
[10 1 1]	0.047	0.120	0.043	0.042	0.100	0.069
[1 10 1]	0.032	0.043	0.012	0.020	0.015	0.021
[1 1 10]	0.022	0.049	0.043	0.027	0.029	0.019
[10 10 1]	0.045	0.091	0.026	0.025	0.078	0.029
[10 1 10]	0.055	0.018	0.051	0.078	0.036	0.061
[1 10 10]	0.020	0.034	0.034	0.045	0.035	0.020

Problems are tested 7 times by applying different weights of objective function terms to analyze the model sensitivity to reconfiguration costs, changing energy pricing and demand in large size problems. It shows that all parameters play an effective role on system reconfiguration. The system has more resistance to layout reconfiguration by increasing the weight of reconfiguration cost (less number of blue cells compared to other weight in the objective function). While applying greater weights to energy and material handling costs persuade the system to have layout reconfiguration in order to minimize the system cost. It verifies that changing energy pricing and demand fluctuation greatly influence on the reconfiguration plan.

Problem No.	Location (L)	Weights of Obj.F. w= [1 1 1] Time periods (t)				Weights of Obj.F. w= [10 1 1] Time periods (t)				Weights of Obj.F. w= [1 10 1] Time periods (t)				Weights of Obj.F. w= [1 1 10] Time periods (t)				Weights of Obj.F. w= [10 10 1] Time periods (t)				Weights of Obj.F. w= [10 1 10] Time periods (t)				Weights of Obj.F. w= [1 10 10] Time periods (t)			
		t=1	t=2	t=3	t=4	t=1	t=2	t=3	t=4	t=1	t=2	t=3	t=4	t=1	t=2	t=3	t=4	t=1	t=2	t=3	t=4	t=1	t=2	t=3	t=4	t=1	t=2	t=3	t=4
p1	l=1	M1	M1	M1	M1				M3	M4	M4		M4	M3		M4	M2	M2	M2	M2	M3		M3	M3	M3	M4	M4	M5	
	l=2	M2	M2	M4	M4	M4	M4	M4	M4	M2	M2		M5	M2	M3	M5	M4	M4	M4	M4	M4	M1	M1			M2	M5		M4
	l=3	M3			M3		M5	M5	M1	M5		M2	M3	M1	M4	M3	M5	M3	M3	M3	M2	M3		M2	M2	M1	M1	M1	M5
	l=4	M4	M4		M5	M5				M3	M3	M3	M2	M5		M2	M3	M1	M1	M1	M1	M5		M4	M4	M3	M3	M2	M2
	l=5	M1	M3	M5	M2	M2	M2	M2	M2	M1	M5	M5	M1	M4	M2		M1	M5	M5	M5	M5	M4		M3	M3	M5	M2	M4	M3
	l=6	M2		M2	M2	M3	M3	M3		M4	M4	M4	M4	M2	M3	M4	M2	M4		M4	M4	M4	M4	M4	M4	M4		M4	M4
p2	l=1	M1		M1		M3	M3	M3	M3	M2		M3		M5		M1	M4	M4		M3	M3				M2	M2	M3		
	l=2	M4	M4	M3		M2	M2	M2	M2	M3		M5	M3	M3		M2	M2		M4	M2	M2	M5	M5	M3	M3	M4			M2
	l=3	M3	M3	M5	M2	M4	M4		M4	M4	M2	M2	M2			M4	M3				M4	M3	M3			M5		M1	M1
	l=4	M2		M2	M1	M1		M1	M1	M1	M4					M3	M5	M5	M5	M5		M2	M2	M2	M1	M1	M4	M2	M3
	l=5	M5		M4	M3	M5		M5				M1	M1	M2	M3		M1	M1	M1	M1	M1	M1		M1		M3		M4	M5
	l=6	M3	M3	M3	M3						M3	M3	M4	M1		M3	M3	M3	M3	M3	M3					M1		M3	
p3	l=1	M4				M4	M2	M2	M2	M4	M3	M2	M2	M4	M4	M3		M5	M5	M2	M2	M5	M4	M4	M3				M4
	l=2	M2	M2	M4	M2	M3	M3	M3	M3	M2	M2	M3	M5	M3	M3	M5		M2	M3	M3	M3	M1	M5	M5	M5	M3	M2	M2	M3
	l=3	M3	M4		M5		M4	M4	M4	M3	M1		M3			M3	M4	M3	M4	M4	M4	M2	M2	M2	M4	M4	M4		
	l=4	M5		M2		M1	M1			M1	M5	M4	M1	M5	M2	M2	M5	M1	M1	M1	M1	M4	M3	M3	M2		M3	M4	M5
	l=5	M1	M1	M3	M4	M5	M5		M5	M5	M4	M1	M4	M2	M1	M4	M2	M4	M2	M5	M5	M3			M1	M2		M3	M2
	l=6	M3	M3	M3	M3	M2	M2			M4	M1	M3	M3	M4	M4		M5	M5	M5			M5	M5	M5	M5	M5	M5		M4
p4	l=1				M3	M3	M3		M1		M3	M2	M5	M1	M2	M1			M5			M3	M3			M2	M1	M3	M3
	l=2		M5	M4	M4				M3	M5	M2	M4	M4	M4	M1	M3	M3	M3	M3	M4	M3	M1	M2	M2	M2	M4	M4	M4	M2
	l=3	M2	M2	M2	M2	M4	M4	M4	M4	M2	M1	M5	M2	M2	M3	M4	M1	M2	M2		M5	M4	M4	M4	M4	M5	M3	M1	M4
	l=4	M3	M4	M5	M5		M5	M1		M1	M4	M1	M1	M3		M2	M4	M1			M4	M5			M5	M3		M2	M1
	l=5	M5		M1	M1	M5	M1	M5	M5	M3	M5	M3	M3	M5	M4	M5	M5	M5	M4	M1	M1	M2	M5	M5	M1	M1	M5		M5
	l=6	M3	M3	M2	M2	M3	M3	M3	M2	M2	M2	M2	M3	M4	M2	M1	M2	M2	M2	M2	M2	M4	M3	M3	M3	M3	M2	M2	M5
	l=7	M4	M3	M3	M3	M2	M2			M4	M4	M3	M4	M3	M2			M3	M3	M3	M3	M3	M3	M3	M3		M2	M3	
	l=8		M4	M4		M2	M2	M2	M3	M3	M3					M3		M3		M2	M2				M3		M4		
p5	l=1	M2		M1	M2	M3	M3	M3	M1		M1			M3		M3	M3	M1					M2	M2	M3	M2		M3	M2
	l=2	M5	M5	M4	M4	M5	M4	M4	M2	M5	M5	M2	M1	M4	M4	M5		M2	M2	M2	M5	M4	M4	M4	M2	M3	M4	M4	M3
	l=3	M4	M4	M3	M1	M1	M5	M5	M3	M3	M3	M4	M2	M2	M5			M5	M4	M4	M4	M5	M4	M5	M5	M4	M2	M5	
	l=4	M3	M3			M4	M1	M1	M5	M2		M3	M3		M1	M1	M2	M4	M5	M1	M1		M3	M3			M1		M5
	l=5		M1	M5	M5	M2	M2			M4	M2	M1		M1	M2	M4	M5		M1		M2	M2	M5	M5	M5	M1	M3		
	l=6	M1	M2	M3	M3		M4	M4	M3	M4	M4	M2	M2	M2	M3	M3		M1	M4	M4	M4	M3	M3	M4		M2	M2	M1	M5
	l=7	M2	M2	M2		M3		M2	M2	M3	M2	M5	M4	M3	M2	M5	M3		M3	M3	M3	M3	M1	M3	M3	M1	M4	M3	M3
	l=8		M3	M3	M3		M3	M3	M4	M4		M2	M5				M4	M3		M3	M3	M2					M3		M4
p6	l=1	M4		M1	M5	M1	M1	M1	M1	M1	M4	M5	M2	M5	M6		M2		M1		M3		M3	M1	M1				M3
	l=2	M5					M3	M3		M6		M4	M6		M4	M6	M4	M2	M3			M2	M2	M2	M2	M1	M5		M4
	l=3		M5	M3	M2	M3		M2	M2		M3		M5	M2	M5	M1	M5	M5	M5	M5	M5	M5	M5	M5	M6	M4	M6	M4	M5
	l=4		M4		M1	M6	M6	M6	M6	M5	M2	M2	M1	M1		M4	M3			M2	M2	M1	M1	M3		M3	M3	M3	M6
	l=5	M6	M6	M6	M5	M2	M2		M1	M4	M1	M1	M3	M3	M2	M3	M6	M6	M6	M6	M6	M3	M4	M4	M3		M1	M6	M2
	l=6	M1	M1	M2	M6	M5	M5	M4	M4		M6	M6	M4	M6	M1	M2	M1	M1	M4	M1	M1	M6	M6	M6	M2	M5	M2	M1	M1
	l=7	M4	M4	M4		M5	M5	M5	M5	M4	M1	M1		M4	M6		M5					M4		M6	M6	M6	M4	M3	M3
	l=8					M2	M2	M2		M1	M6	M1				M5		M3	M4			M6	M6			M5	M4	M5	M4

Figure 20 - Layout Configuration –large size

Blue cell represents layout reconfiguration between two consecutive time periods

CHAPTER 7

Conclusions and Future work

6.1. Concluding Remarks

Three novel linear mathematical models are presented in an evolutionary basis to analyze the influence of changing energy price in reconfiguration decisions.

A new linear mixed integer mathematical model proposed to configure the manufacturing system to make it more efficient and maximize its sustainability on an operative level. Three main elements are considered in the first model which affect system sustainability in the both environmental and economic point of view. These three factors are the change pattern in energy prices during a day, transportation cost of jobs moving from one machine to another and the setup cost of each machines. Result of the proposed model is a system configuration plan which shows machines arrangement and job sequences. To get the result out of the proposed model GAMS CPLEX solver has been used for nine different problems in size. The new linear mixed integer model finds the optimum system configuration plan in a reasonable time. This output depicts the efficiency and practicality of the proposed model.

In the second model, the influence of changing energy price in reconfiguration decisions is considered from a bigger-picture perspective. A new linear mixed integer mathematical model is proposed to select the most efficient system configurations in mid-term periods to maximize system's sustainability and reconfigurability on the structural level based on trading-off between energy consumption and configuration costs. GAMS CPLEX solver is applied to solve the proposed model for nine different problems in size. The model finds the best selected system reconfiguration including layout configurations and process routings for each mid-term period (e.g. season) in a reasonable time. In this model, changing energy price between and within seasons and demand fluctuation in each season are considered which affect system sustainability and reconfigurability. This output shows that unstable energy pricing and demand variation affect layout and material handling system reconfiguration selection. In other words, the cost of changeability is not only dependent on the difficulty of the system convertibility from a configuration to the next, but also on what time of the year during which it is performed and degree of scalability the system has, since energy pricing and demand changes throughout the planning horizon.

Finally, a comprehensive model is proposed to analyze the effect of changing energy pricing within and between periods in reconfiguration decisions. A novel linear mixed integer mathematical model has been presented to minimize the total energy consumption cost (MILTEC), which has been solved to maximize the sustainability of RMS, integrating machines configuration and operation scheduling decisions under a volatile environment, in which energy pricing and demand are changing throughout a multi-period horizon. The novelty of the MELTEC model is the consideration of the changing energy price effect simultaneously on the system configuration and operation schedule decisions. The MELTEC model determines the optimal operation scheduling, alternate process routings, completion time for each product, and machine configuration including purchasing machines, duplicating machines, and machine arrangement at each period (e.g. season) over the long-term planning horizon (one year). The optimal solution is found through minimizing total costs of energy consumption, machines reconfiguration, and part transportation between machines, which all depend on fluctuations in energy pricing and demand during the time. Energy consumption cost is calculated by considering the amount of energy consumption for each task and the corresponding energy price based on what time duration the energy has been consumed. Machines reconfigurations cost is calculated based on purchasing and relocating machines costs over the time. Transportation cost is evaluated based on distances between machines and production volume.

The new model has been evaluated using 12 test problems with 7 different weights of objective function terms which half of them are also solved 5 times (total 252 runs) through using an optimization method in GAMS and GA algorithm in MATLAB to show the efficiency of the model. Results have been analyzed from different aspects of objective function, computational time (table 14, table 16), and layout configurations (Figure 12, Figure 19). GAMS software found optimal solutions in a reasonable time for problems in small size. Since the model is considered as NP-hard, an efficient genetic algorithm (GA) is extended to solve the proposed model on a larger scale. The GA algorithm performance has been statistically evaluated and compared to GAMS results based on the best objective function value, the average objective function value, the standard deviation of objective function value, and computational time factors (table 18, table 20). It is shown that GA found near optimal solutions in a far less time than GAMS computational time with an insignificant gap to optimal. Results of solving problems in large size also demonstrated the GA efficiency due to presenting robust performance over several runs.

Problems are tested 7 times by applying different weights of objective function terms to analyze the model sensitivity to reconfiguration costs, changing energy pricing and demand. It demonstrates that all parameters play an effective role on system reconfiguration. Figures 12 and 19 show that the model does not reconfigure the layout when the weight of reconfiguration cost is greater than other costs (less number of blue cells in figure 19 compared to other weight in the objective function). While applying greater weights to energy and material handling costs forces the system to reconfigure the layout to minimize the overall system cost. It verifies that changing energy pricing and demand fluctuation greatly influence on the reconfiguration decisions.

Therefore, the thesis of this work states that energy price fluctuation has a considerable optimizable effect on manufacturing system structural and operational decisions. It means that the reconfiguration cost does not only depend on the degree of system changeability but also can depend on the time during which it is performed due to the energy price fluctuation. Based upon this work, it is recommended to consider environmental and operational parameters like energy price fluctuation alongside with other factors related to degree of system changeability in the both structural and operational decisions in CMS, since these two levels of decision can be interrelated. For instance, the energy price fluctuation not only affects scheduling and sequencing decisions (operational decisions), but also layout configuration decision which is in a structural level.

The main advantage of the proposed model is finding an optimum solution in a very reasnoable time, while it consideres energy sustainability concurrently with system configuration and operation schedule decisions with the aim of total cost minimization. Regarding the limitations of the model, it should be noticed that mathematical models are inherently inexact, since they represent a version of real situations. Its description or our perception can be inadequate. Parameters used in this work are assumed deterministic to simplify the proposed mathematical model. While many of these parameters practically are uncertain.

6.2. Future work

The presented MILTEC model can be used by researchers and practitioners to design sustainable changeable manufacturing systems in practice. Furthermore, the MILTEC model allows the incorporation of other features, such as idle time cost, machine redundancy, breakdowns, accounting for other sustainability domains such as technological and social domains, introducing robust approaches to overcome uncertainty in demand, energy pricing, machine availability, etc. which can be considered in future research work.

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