Optimization of the Scheduling Strategy Using Meta-Heuristics Approach in the Context of Cellular Manufacturing with Multiples Products

by

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Optimisation de la stratégie d'ordonnancement en utilisant l'approche méta-heuristique dans le cadre de la fabrication cellulaire avec de multiples produits.

Mahmoud ALZIDANI

RÉSUMÉ

La planification de la production est au cœur du système de planification et de contrôle. Parmi les solutions les plus intéressantes on trouve la fabrication cellulaire (Cellular Manufacturing Systems CMS). Le CMS est un système structurel basé sur la théorie des groupes. Son concept présente plusieurs avantages, notamment la réduction du temps total d'exécution et du temps d'écoulement. La planification de la fabrication cellulaire est un problème d'optimisation NP-difficile. Selon la taille du problème, le nombre de machines et le nombre de pièces, le temps de calcul nécessaire pour obtenir la solution optimale augmente de façon exponentielle. Pour résoudre les problèmes d'optimisation de ce type, les algorithmes métaheuristiques sont jugés les meilleures pour obtenir des bonnes solutions dans un temps raisonnable. Dans ce travail, nous proposons une nouvelle méthodologie pour optimiser la séquence des pièces dans chaque cellule de fabrication, y compris les articles exceptionnels. Cette technique est basée sur l'algorithme RC-Filter. La méthodologie proposée a permis de minimiser le temps requis. Elle a été validée à l'aide de treize problèmes tirés de la littérature. Les résultats ont été comparés à ceux fournis par le Grand Déluge étendu. Comme la fabrication cellulaire est un système structuré basé sur le concept de groupe, il a plusieurs avantages comme la réduction du temps de production. Le problème de l'optimisation étant classé NP-difficile, le temps de calcul augmente exponentiellement avec la taille du problème. L'utilisation des algorithmes métaheuristiques est une excellente solution pour la résolution dans un temps raisonnable. Dans ce travail, nous avons proposé une nouvelle approche hybride pour optimiser la séquence des pièces dans chaque cellule ainsi que les éléments exceptionnels. La méthodologie hybride proposée est basée sur l'algorithme RC-Filter et l'algorithme Extended Great Deluge. L'outil proposé est utilisé pour optimiser la séquence des pièces y compris les éléments exceptionnels dans chaque cellule afin de minimiser le temps total d'exécution. L'approche proposée a été validée en utilisant 13 problèmes et les résultats ont été comparés à ceux fournis par d'autres algorithmes. Un environnement de fabrication cellulaire est généralement l'environnement le plus efficace en termes de minimisation du temps total d'exécution, du temps de passage et de la manutention. Par contre, dans la plupart des cas, un environnement de production cellulaire nécessite l'exécution d'éléments exceptionnels. Cette tâche génère de nombreux retards et mouvements intercellulaires. Ce problème est considéré comme un défi important à résoudre afin d'atteindre non seulement le temps d'exécution minimum, mais aussi les mouvement intercellulaires. Dans ce travail, une méthodologie a été proposée, appelée l'algorithme méta-heuristique de recuit simulé, afin d'obtenir la meilleure séquence de pièces, qui permet d'obtenir le temps d'exécution minimum. Ce travail a été divisé en deux étapes et chaque étape contient deux parties: Dans la première partie de la première étape, nous avons utilisé le recuit simulé pour trouver la meilleure séquence d'éléments exceptionnels sans changer l'architecture de la cellule. C'est une étape d'optimisation comme un problème des ateliers à cheminements multiples (Job Shop), car il y avait beaucoup de mouvement intercellulaire. Dans la deuxième partie, nous avons optimisé la séquence dans chaque cellule. Pour réduire les mouvements intercellulaires, nous avons utilisé un environnement cellulaire dynamique. Dans la deuxième étape de ce travail, nous avons utilisé une cellule de fabrication dynamique. Cette étape comporte deux parties. Dans la première partie, de snouvelles cellules ont été conçues en utilisant uniquement des éléments exceptionnels. De même, les machines utilisées pour fabriquer les éléments exceptionnels ont été transférées dans d'autres cellules. Au cours de la première partie, les éléments exceptionnels ont été fabriqués à partir d'une architecture de cellule spécifique. Le but de cette partie était de donner le minimum de mouvements et de manipulations intercellulaires. La deuxième partie de cette étape consistait à sauvegarder la configuration des cellules d'origine et les séquences de pièces ont été optimisées dans chacune d'elles. L'optimisation des séquences de pièces a été réalisée à l'aide de l'algorithme de recuit simulé. Mots clés : fabrication cellulaire, algorithme méta-heuristique, temps total d'exécution, éléments exceptionnels.

Mots-clés : fabrication cellulaire, algorithme de méta-heuristique, makespan, éléments exceptionnels.

Optimization The Scheduling Strategy Using Meta-Heuristics Approach in The Context of Cellular Manufacturing with Multiples Products,

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ABSTRACT

Production scheduling is at the heart of the plant's planning and control system. One of the attractive production planning systems is Cellular Manufacturing Systems (CMS). CMS is a structural system based on group theory. Several advantages of the SFC concept mainly include the reduction of makespan and flow time. CMS is an NP-hard optimization problem. Depending on the size of the problem, the number of machines, and the number of parts, the computing time required to obtain the optimal solution increases exponentially. To solve NP-hard optimization problems, metaheuristic algorithms are the best solution to get good solutions in a reasonable time.

In this work, we propose a new methodology to optimize parts' sequence in each manufacturing cell, including exceptional items. This technique is based on the RC-Filter algorithm. The proposed methodology was used to optimize the sequence of parts, including exceptional items, to minimize the time required. The proposed approach has been validated using thirteen problems taken from the literature. The results were compared to those provided by the Extended Great Deluge.

A cellular manufacturing system is a structured system based on the concept of a group. One of the advantages of this concept is that it can reduce production time. Optimizing cell manufacturing systems are categorized as NP-Hard, where the computational time increases exponentially with the problem's size. Utilizing metaheuristic algorithms will be an excellent solution to solve the NP-Hard problem in a reasonable time. In this work, we proposed a new hybrid approach to optimize the sequence of parts in each cell and exceptional elements. The proposed hybrid methodology is based on the RC-Filter algorithm and the Extended Great Deluge algorithm. The proposed tool is used to optimize the sequence of parts, including exceptional items in each cell, in order to minimize makespan. The proposed approach was validated using 13 problems, and the results were compared with those provided by other algorithms. A cellular manufacturing environment is generally the most efficient environment for minimizing makespan, flow time, and handling.

On the other hand, in most cases, a cell production environment requires distinctive elements' performance. This task generates many delays and intercellular movements. This problem is seen as a fundamental challenge to be solved to achieve the minimum makespan with exceptional elements and the minimum intercellular movement. In this work, a methodology was proposed, called the simulated annealing meta-heuristic algorithm, to obtain the best sequence of parts, allowing the minimum makespan.

This work has been divided into two steps, and each step contains two parts; these steps are as follows:

In the first part of the first step, we used simulated annealing to find the best sequence of exceptional elements without changing the cell's architecture. This is an optimization step as a jobshop problem, as there was much intercellular movement. In the second part, we optimized the sequence in each cell. These two parts represent the first stage of this work. To reduce intercellular movements, we used a dynamic cellular environment. In the second step of this work, a dynamic manufacturing cell was used. This step has two parts. In the first part, new cells were designed using only exceptional elements. Likewise, the machines used to manufacture exceptional items have been transferred to other cells. During the first part, the exceptional elements were made from a specific cell architecture. The goal of this part was to give the minimum of inter-cellular movements and manipulations. The second part of this step was to save the original cells' configuration, and the part sequences were optimized in each of them. Part sequence optimization was performed using the simulated annealing algorithm.

Keywords: cellular manufacturing, meta-heuristics algorithm, makespan, exceptional elements.

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LIST OF ABBREVIATIONS

RC-Filter	Resistor Capacitor Filter
EGD	Extended Great Deluge
SFC	Shop Floor Control
NP	Non-deterministic Polynomial-time
SA	Simulated Annealing
GA	Genetic Algorithm
ACO	Ant Colony Optimization
ABC	Artificial Bee Colony
CMS	Cellular Manufacturing System
BB	Branch and Bound
MIP	Mixed Integer Programming
EVIS	Evolutionary Intra cell Scheduler
LCS	Learning Classifier System
VNS	Variable Neighborhood Search
JSSP	Job Shop Scheduling Problem
FCFS	First Come First Served
SPT	Short Processing Time
EDD	Earliest Due Date
CR	Critical Ratio
SPRO	Slack per Remaining Operations
EE	Exceptional Element
SVS	Singing voice Separation

LIST OF SYMBOLS

S_0	Initial solution
N(s)	Neighborhood solution set
ΔB	input parameter (step used to decrease the limit B)
S	Random solution
α	Efficiency of the solution S
N	Neighborhood solutions of S.
S*	Neighboring solution randomly selected from the set N
ti	Original value of the data point i
n	the number of jobs
m	the number of machines
tji	the processing time of job j on machine i .
s	the set of jobs
q(s, i)	the completion time
s	on machine i .
Fs	the flow time of all jobs in s

INTRODUCTION

In the ever-growing fast-changing world, it is really important to focus on timing, cost, and efficiency. The world is getting more and more global with every passing day and has impacted the way business is run worldwide. In order to compete with the lowering cost market over the globe, businesses are taking more interest in cellular manufacturing approaches instead of conventional approaches.

In the conventional departmental manufacturing environment, any job travels in multiple work centers which have been dedicated to finishing a single task in the general procedure of manufacturing. This type of setup borrows itself to the given batch and queue processing, which results in jobs with enhanced travel times and waiting times and hence much longer lead times. In a cellular manufacturing approach, numerous work cells work together in order to develop a manufacturing space. Each of these cells has the capability to significantly perform all steps of the manufacturing process. Once a cell starts to perform a job, every step in the process ensues till the job is done. In this type of manufacturing process, the flow is promoted by the setup where cells work together, which results in minimum waiting and travel times, lesser lead times, and better responses to the customers.

0.1 Production Scheduling

The next step in the transition to cellular manufacturing is the optimization of the scheduling of cell jobs. Each cell has different parameters like skills, cost, and capacity. Each job has different outcomes like profit, specifications, due date, and production requirements. The job scheduling tools such as ActiveBatch, Tidal Workload Automation, IBM Workload Automation, etc., allow the real-time scheduling of the cells based on the current as well as the forecasted jobs. Also, with the frequent expedited orders, the scheduler must be able to handle the completion of these jobs in a very short period of time, especially in a case where the capacity is low. This research will focus on the optimization of the scheduling mechanisms in order to reduce the makespan. It will help the manufacturers to schedule their jobs to improve their schedule throughout their units so that they can fulfil the ever-changing demands of their customers while maintaining their key strategies. It is imperative that production processes are optimally regulated in the dynamic industrial climate. This requires manufacturing firms to reduce costs of production and to comply with production schedules. This shows the need for expensive, time-consuming shop floor reorganization and enables a rapid reaction to change conditions and requirements (Nomden and Slomp, 2006). The production schedule today is the center of the factory's planning and control system.

Many researchers have focused on research related to work schedules. Many heuristic approaches and traditional optimization tools have been deployed to study scheduling issues. The authors (Golenko-Ginzburg and Gonik, 2002) tried to determine the best time for starting the processing jobs. The jobs are processed on the same equipment on random time durations. Late submission of the job has penalties, as well as early submissions, have inventory cost penalties as well. Another research was carried out by (Dennie 2006), where each job had early dates, due dates, urgency constraints, and precedence constraints. Each job had one or more operations. An initial solution is developed by satisfying all the constraints quickly and trying to keep maximum utilization of machines and work in process as minimum. The jobs are assigned to machines and then an improvement is made in the procedure accordingly.

A group of researchers performed simulation studies by using a weighted slack rule which aimed to reduce the maximum weighted tardiness and weighted flow time of the job (Thiagarajan and Rajendran, 2005). Another team of researchers used the makespan criterion to study in the proximity of no-wait job scheduling issue (Pasupathy et al., 2006). The waiting between the executions of consecutive operations of the same task is not allowed. The decision rules are favourable in scheduling as they are easy to understand, simple to relate to the problem and help in improving the solving time. However, they are not good enough for the problems of bigger complexity and magnitude. These rules, however, do not give an optimal solution for the problems and their variance from the optimal solution increases as the complexity of the problem increases. Therefore, the development of a decision rule may not be the best option for a heuristic to help in the solution of cellular job scheduling issues.

Mathematical programming is also used by some researchers for scheduling. Integer and linear programming more specifically fall into this category. It has the benefit of the achievement of complete enumeration of the problem, and hence an optimal solution can be achieved. Manufacturing systems where a wide variety of products of multiple volumes are to be produced on a tight due date were investigated by (Lengyel et al., 2003). A feasibility function is a new algorithm for scheduling that is related to the due date. It was used with more than five thousand jobs and fifteen machines by simulation in order to showcase the scheduling algorithms' behaviour. The aim was to balance the tardiness and earliness jobs so that the difference between the minimum and maximum delay of jobs can be reduced. The results showed the benefits of using the feasibility functions for scheduling purposes. The authors (Arakawa et al., 2003) used an optimization-oriented method for scheduling simulations related tasks for reducing the delayed jobs in an integrated capacity adjustment. The technique integrated the parameter-space search-improvement with the scheduling mechanism.

CPLEX- computed and self-tuning dynP job schedulers were compared by (Grothklags and Streit, 2004). In the dynP scheduler, the active scheduling policy is changed dynamically in order to reflect the changing features of the waiting jobs. In the CPLEX method, an integer problem was developed. The time schedule was deployed, which helped to compute the schedules on a larger than one precise scale. The results of the comparison showed that each method provided very similar solutions, but the dynP scheduler provides a solution in a very short time as compared to the CPLEX method. The authors (Mati and Xiaolan Xie, 2003) used a polynomial algorithm for two-job shop scheduling with flexible scheduling. The routing of scheduling jobs is not fixed and must be determined from multiple options. The algorithm developed by (Mati and Xiaolan Xie, 2003) is based on a geometric method and deploys dynamic programming to build a network that can determine the optimal solution. The algorithm can be applied to any minimizing objective function. The developed algorithm can also be modified to fit multi-resource operations.

The mathematical programming techniques are beneficial as they achieve an optimal solution, but the time taken for the solution is excessively high. This disadvantage outweighs the benefits created by the optimal solution. Solving cellular job scheduling is not a very easy and simple task. The multiprocessor problem was found out to be NP-complete by a polynomial transformation by the partition problems; the NP-complete is a decision problem that can be resolved by an annon-deterministic algorithm in polynomial time (GFG, 2020). The manufacturing facilities work in diverse environments. The orders can be expected at any time, and the manufacturing floor should be able to accommodate the new job from the new order. Hence, it may not be suitable to compute all the points in the problem completely. The manufacturing facility required a real-time solution schedule. The solution technique should offer an almost optimal solution in a satisfactory amount of time. Numerous methods, like genetic algorithms, greedy approaches, neighbourhood relations, and search methods, have been developing aiming at the solution of job scheduling issues with mixed results.

The authors (Kim and Lee, 1994) used heuristic hybridization and genetic search to provide a computationally feasible solution for a job scheduling problem. A tree search procedure-based heuristic was developed for job scheduling aiming at minimizing the total weighted tardiness (Asano and Ohta, 2002). Every job has its pre-defined deadlines and penalties for delay. The schedule is determined using minimizing the maximum tardiness. This tardiness is subjected to a number of fixed schedules that are solved at each node of the search tree, and then the successor nodes are developed on which the sub-schedules of the required operations are fixed. In this way, a schedule is developed at every node, and a sub-optimal solution is calculated at the obtained schedules. The results of this algorithm show that the solution with minimal time for the computation was found. The authors (Zhou et al., 2001) developed a hybrid heuristic genetic algorithm in which scheduling rules like most working remaining and the shortest processing time were combined in the genetic evolution problem. The Variable Neighborhood Search (VNS) method was used as an add-on procedure in order to improve solution performance. This technique was found out to be efficient and effective as compared to other methods like simulated annealing and traditional genetic algorithm. The authors investigated a job scheduling method by deploying group constraints, which means that the schedule for jobs in each line is already decided, and the jobs dealing with the same tasks must be grouped together (Ohmae et al., 2003).

This planning activity is generally a complex task and becomes particularly more sophisticated in the context of the high technology manufacturing system and of mixed production (multi-products). Group Technology (GT) has been introduced to simplify the scheduling process: the manufacturing jobs are grouped into job families and processed as groups through a cellular manufacturing system (CMS). This procedure was studied by (Suzić et al., 2012). The authors presented a way for product customization using the application of group technology. It provides the machine and product groups and hence simplifies the material flow.

If the machines were grouped, the term cellular manufacturing is being used to define the organization's process. Cellular manufacturing is an application of group technology in which different machines or processes have been aggregated into cells. However, those cells of which are dedicated to production are part of the product family.

0.2 Scheduling strategy & Group Scheduling

The scheduling in this context is called "Group Scheduling" (GS). Generally, the principal aim of the scheduling strategy is to find out the best sequence of manufacturing operations, which minimizes the total manufacturing cost and completion time. In the context of multi-demands and multi-products manufacturing today, the GS strategy must be dynamic and flexible for application. *Good scheduling* is strategy to furnish out an optimal schedule with shortest operating time & lowest cost.

0.3 Meta Heuristics Approach

To find out the solutions to this problem with the classic approaches requires a great number of computations, and sometimes the optimal solution cannot be found. The Meta-heuristics approach is a potential alternative for the solution of complex scheduling problems, particularly in the case of large-scale problems. The power of the Meta-heuristics techniques resides in the fact that they have a great capacity and efficiency of computation and high application flexibility in solving complex optimization problems, such as scheduling problems because this problem is considered as NP-hard (non-deterministic polynomial-time hard), it is not a decision problem which can be solved without non-deterministically (GFG, 2020).

0.4 Research outline and objectives

0.4.1 Problem statements and motivations

The problem which has been tackled in this thesis is scheduling optimization in the manufacturing business. However, the difficulty of this study was both to find out the best metaheuristic among many types of them, which will help to support this thesis to be completed and also the methodology which will be applied in order to obtain the minimum completion time (makespan). This solution has two stages that were discovered by many researchers who have been developing the metaheuristics technique for decades. Usually, the first stage seeks the sequence of parts within the groups (cell), and the second stage concentrates on finding out the sequence of groups (cell).

The motivation behind this study as a researcher in the field of manufacturing to optimize the schedule is due to the huge demand and rapidly increased manufacturing business. As a researcher, the next step after graduation is looking for a job; being in this domain of scheduling optimization would attract many employers to hire me. Nowadays, more than two-thirds of the world's economy depends on the manufacturing business. Working in this field has a huge impact on me personally, both scientifically and practically, for future doors to be opened. Scientifically, I would be concentrating on article publications in many respectful journals and well ranked; this part can add great value to my scientific reputation.

0.5 Problem description

The problem is clearly and concisely defined in this study as scheduling optimization in the field of manufacturing, specifically in the production process. Nonetheless, this problem is considered an NP-hard problem, which required a high technique called metaheuristic to solve it. First, to find out the best metaheuristic approach among many others, which will help us to resolve the problem and provide optimized scheduling. On the other hand, the problem is also with the methodology; we need to find a precise method that can provide the minimum makespan.

0.6 Objectives and the scope of the study

In general, the objectives are very important to be determined before starting any project or any study in order not only to make the proper decision but also to govern all the required resources and tools to achieve those objectives. Setting up the objectives as early as possible will help to achieve a successful result. The scheduling problem is considered a nightmare for many business organizations which their jobs are required to use a cellular manufacturing system (CMS) in their production facilities, especially with multi-products because it is well known as an NP-hard problem, in computational complexity theory is a class of problems that are informal, "at least as hard as the hardest problems in NP." Therefore, an enormous amount of research is being conducted throughout the last two decades to find out what the best solution could be obtained so that the issue would be solved or optimized. However, the key objective behind this researche is either to save time or to reduce the cost, which eventually would lead to maximizing the organization's profit. Hence, the main objective of the study is to develop a scheduling strategy following by adjusting a current mathematical model for a metaheuristic algorithm in order to minimize the Makespan via MATLAB to obtain the optimal results.

CHAPTER 1
LITERATURE REVIEW

The major factor that affects the scheduling of both continuous and batch process industries is the efficiency of processing operations in manufacturing systems. However, several constraints and factors add to the complexity of scheduling in process industries; these include a network of equipment, complex production procedures, limited storage capacity, material transport, and limitation of resources. Therefore, a variety of research has been carried out in order to analyze and propose different methods for optimizing and scheduling manufacturing systems in process industries. A review presented by (Hazaras et al., 2012) consolidates the related research over a vast period of time. Figure 1.1 shows the classification of these methods, where the two main categories are: Mathematical Programming and Metaheuristics. These can further be divided into Mixed Integer Programming (MIP) and Deterministic and Stochastic methods.

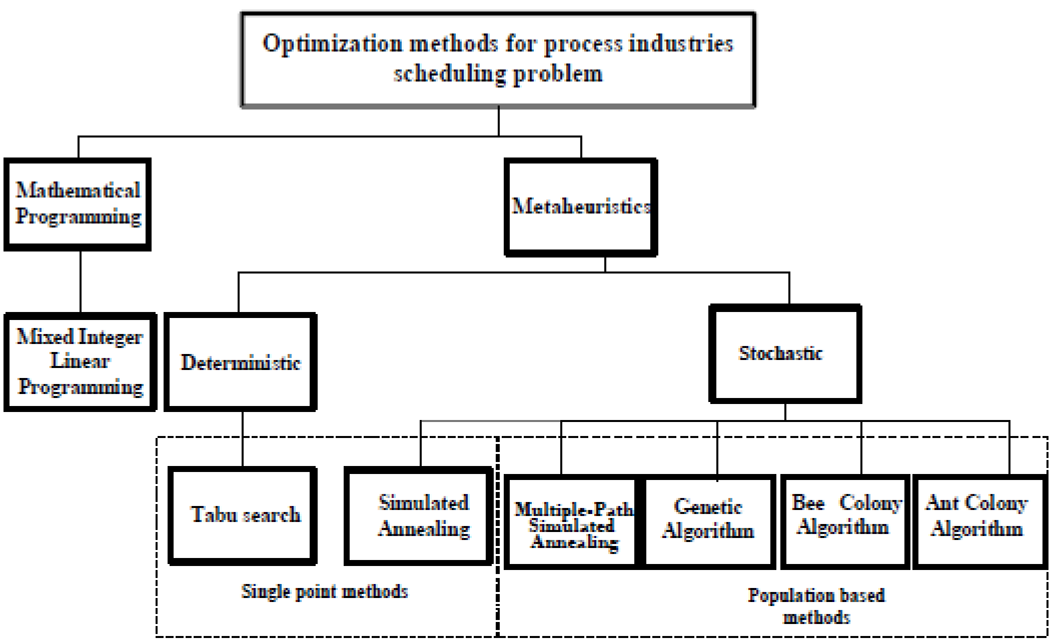

Figure 1.1 Flowchart of scheduling methods in process industries (Jalalian, 2018)

1.1 Scheduling methods

Scheduling can be described as allocating resources for the performance of tasks over time. The importance of good industrial scheduling plans in today's competitive markets can't be extravagant. The need for rapidly satisfying customer's demands and effective management of plants contributes to complex planning challenges in all but the easiest manufacturing environments. Many manufacturing facilities are being affected by buzz words such as constancy, suppleness, toughness, adaptability, and efficiency; therefore, it is very important that production facilities be optimized, especially in scheduling. There have been substantial progressions in parts factories, as well as enhancements in both precision and tractability of controlling machines for the production process or layout facility.

The production schedule is being strengthened by the utilization of optimization algorithms and the implementation of advanced software systems hence increasing the manufacturing plant's efficiency. In these development environments, a cellular manufacturing system (CMS) has evolved in labor-intensive industries. It has several advantages, such as reducing production costs, reducing production time, and improving production flexibility, and in recent years it has attracted increasing attention. Cell development and product design are considered to be two of the main problems. The first includes the transfer of goods and equipment (workers). The second conducts the process of dispatch and scheduling of items. Moreover, solving the group scheduling problems required two stages by researchers who have been developing the metaheuristics technique for decades. Usually, the first stage seeks the sequence of parts within the groups (cell), and the second stage concentrates on finding out the sequence of groups (cell). Thus, many researchers and publications focused on the analysis of manufacturing cell problems. The majority of these studies discuss and analyze static manufacturing cells. There are three planning tasks that are necessary for the manufacturing cell environment (Wu et al., 2007) & (Akturk, 2011). These three tasks can be solved independently. The first task is to group the machines that will make a family of similar parts; the obtained groups represent the manufacturing cells. The second task is to solve a layout problem. The cells should be positioned in the workshop, and the machines should also be positioned in each cell. The third task is the scheduling problem; the sequence of the parts has to be optimized in each cell. This task becomes more complicated when we have exceptional elements where some parts have to be manufactured in more than one cell. The first and the second task have been given more attention by researchers (Wu et al., 2009), (Papaioannou and Wilson, 2010) & (Kia et al., 2012). On the other hand, some researchers focus on scheduling problems to proposed tools in order to get full benefits of the manufacturing cell systems, especially with an exceptional element, which is the aim of our work (Janis and Bade, 2016). Moreover, "a Cellular Manufacturing System (CMS) is a development method in which machines are divided into distinctive cells, and parts are often allocated to these cells for their design, form, purpose, manufacturing process, and more. Consequently, CMS obtains both mass production cost-effectiveness and job shop manufacturing flexibility. The significant advantages of CMS reported in the literature are reduced setup time, reduced work-in-process inventory, reduced throughput time, reduced material handling cost, improved quality and production control, increased flexibility, etc." (Kumar and Ramesh, 2012).

Many researchers proposed several approaches in order to solve group scheduling problems. The majority of these studies analyzed heuristic and meta-heuristic techniques where acceptable results were given to reasonable computation time. Meta-heuristic approaches remain the strong tools for solving this type of problem, ranked NP-hard while minimizing the running time. From a large variety of meta-heuristic tools, we can cite a study proposed by (Zabihi et al., 2019); the authors proposed a tool based on particle swarm optimization approach to "minimize the completion time" by determining the best sequence of jobs in each cell and the sequence of cells. Thereafter, this work was improved by (Liou et al., 2013) by using a hybrid tool based on particle swarm and genetic algorithm with the aim of minimizing and integrating the sum of completion time with removal and job transportation time (Swarnkar and Tiwari, 2004). A methodology was proposed by (Sridhar and Rajendran, 1993) based on a "genetic algorithm with the aim to optimize the family and job scheduling in a flowline-based manufacturing cell. To propose a "solution for group scheduling and machining speed selection problems" (Zolfaghari and Liang, 1999) developed a hybrid tabu search and simulated annealing methodology." (Abdallah and Dao, 2011) used a "meta-heuristic methodology called "Extended Great Deluge (EGD)" to develop an optimization tool to the scheduling manufacturing problem with the aim of “minimizing the makespan and the flowtime” in the manufacturing cell process.” The authors also proposed a solution for exceptional elements. (Sridhar and Rajendran, 1994) proposed a model to “optimize the manufacturing cells and also to minimize the makespan, the flow time, and the idle time. Their solution excluded exceptional elements.” (Solimanpur et al., 2004) proposed a “heuristic called SVS-algorithm to minimize the makespan in getting the optimal sequence of parts in a cellular manufacturing process.” The meta-heuristic algorithm, the ant colony, was used by (Guo et al., 2012) to determine the “optimal sequences of part in a complex job-shop manufacturing environment.” A problem with cell formation is the distribution of component families and machines / workers, and its solution is crucial to maintaining high productivity. Many studies have dealt with this in recent years. (Mohammadi and Forghani, 2017) create a hybrid approach that incorporates genetic algorithms to solve a bi-objective problem of cell formation by exploring alternative process pathways.

The majority of the investigations conducted are based on job scheduling by applying decision rules and regulations. The entire exercise was conducted to ascertain the most advantageous earliest time to commence processing tasks (Kaplanoğlu, 2016). Every task is to be executed on assigned machines in a haphazard time frame. Every task has a deadline and is to be carried out, or else penalties are imposed if they fail to meet the deadline, but it has an associated inventory expense for completion prior to the deadline. Heuristics employed in this issue zooms in on decision making with respect to the unmethodical functioning and expense restrictions. The standard processing period, coupled with the central limit theorem, is applied to ascertain the odds so that the tasks can be completed within the stipulated time frame. These prospects and decision-making rules and regulations are to be applied to ensure and ascertain the related expenses of finishing the task earlier or later.

A group of researchers deliberated the evolution and execution of the task scheduler at a glass industry and a late date (Demir and İşleyen, 2014). Every task consisted of one or more functioning. A primary viable model is created by speedily fulfilling all precedence and limitations of the resources, though proposing to optimize utilization of the machine and minimizing the procedural process. Based on these primary models, tasks were allocated to machines' priority criterion, afterward resulting in an enhanced stage that follows. Also, heuristics like round-robin algorithm side by side tasks, activities next in line were scrutinized. A refashioned criterion due date method was adopted that worked satisfactorily in accordance with the management of tasks within the timeframe. Scheduling norms were put in place for workshops that do not take into consideration the expense of tardiness per piece is one and the same for every piece, and the stocking expenses are incomparable to the beginning of a task (Park et al., 2015). A well-exercised slack rule was applied in order to have a minimal optimum “weighted tardiness” and “weighted variance of the tardiness” of tasks. Another method that was applied is the weighted flow due date, striving to capitulate the least costly for the most flowtime and “weighted variance of the tardiness” of flowtime. A second group scrutinized the estimation of the “no-wait task scheduling issue applying the makespan criterion” (Koulamas and Panwalkar, 2016). In such surroundings, there is no-waiting permitted between the implementations and subsequent activities of the same task. Once in operation, the entire process should be finished operation by operation, without any sort of preemptive. It was observed that the multinomial time estimation idea does not exist. The rules of decision are advantageous to task scheduling, it is because these rules are comparatively easier to understand, quite common to adhere to the issue, and usually enhances the resolution time.

However, issues of the greater immensity and intricacy, the edge of decision rules, somewhat shrinks away. Decision rules are not equipped to suggest the most favorable answer to an issue, and customarily the more complex the issue gets, the farther the decision rule gets from solving the issue. Therefore, heuristics is not an ideal option in resolving cellular job scheduling issues. Another scheduling method is “mathematical programming.” “Mixed-integer programming” and “linear programming” are comparatively more suitable options for such criteria. Mathematical programming is more superior as an absolute particularization of the issue can be acquired, ensuing in a factual, most favorable solution. Researchers scrutinized manufacturing systems that had a wide range of products of different shapes and sizes that are to be made within a pressing due date (Korytkowski et al., 2013). All such units are employing feasibility functions to schedule tasks—linear programming for the multi-machine random workshop. The entire exercise is aimed at creating an equilibrium between tardiness and early tasks. A facsimile model incorporated with multi-agent architecture to permit the contrast of the well-studied feasibility function procedure against the regular rules of scheduling were evolved. The results obtained indicate that for job scheduling, feasibility functions are extremely advantageous. Another method that is optimization-oriented was applied to the "simulation-based job scheduling." It was able to integrate the capacity adjustment (Gansterer et al., 2014). The objectives of this method were to get rid of tardiness in tasks of the manufacturing unit. The suggested option amalgamates "parameter-space-search-improvement" into the scheduling procedures. For coming up with the most favorable blend, a community exploration is conducted to minimize the computational period. The technique was tried out applying data from an already established and implemented wide-ranging system, and the conclusion is that the computation time was prolonged and not up to the desired time.

CPLEX- Job schedules calculations were contrasted to the dynP job scheduler (Grothklags and Streit, 2004). The scheduler vigorously altered the energized scheduling approach for correct observation changes attributes to the pending jobs. An integer version was evolved in the CPLEX procedure. Scaling time was used, which permitted the schedule to be calculated for a greater than a second accurate measure. Observations were cross-compared, and results suggested these procedures ended up providing similar results, with one exception that the self-dynP scheduler gave results far quicker than the CPLEX procedure. A “polynomial-time algorithm” was applied to scheduling for shops that could cater to two jobs with flexible scheduling (Dai et al., 2015). Routing isn't predetermined, and it is to be set on through a number of options. The evolved algorithm relies on geometric perspectives using dynP to build a meshwork that can assist in ascertaining the most favorable option. Such a program can be used for all standard drastic reduction in functional objectives. The algorithm will alter for compatibility with numerous resource procedures. Programming involving mathematics techniques is favorable since it permits acquiring the best possible solution (Aminzadegan et al., 2019). Though, with detailed reciting in ascending order on an NP-Complete issue, the resolution time related to traditional optimizing a mixed-integer program or a linear program will become very lengthy. The downside of a prolonged resolution time of an issue far outweighs the advantages provided to resolve an issue optimally.

1.2 Scheduling strategy

It is the way to perform sequential operations (activities) to realize a job. The degradation of production plan into the ‘time-phased activities’ is the purpose of scheduling. This scheduling will also determine a activities timetable which will optimize predetermined criteria. The three major classes for the criteria of decision making are deadlines close conformance, reducing flow times, and efficient usage of the resources. Furthermore, it is a process of decision making which is an important player in services and manufacturing industries (Xu et al., 2020; Zhou et al., 2020). There are common problems related to scheduling optimization:

1.2.1 Open shop scheduling

One of the major scheduling problems is open shop, where an assigned job set must be completed within the assigned time by each workstation in random order. The main purpose of open shop scheduling is to find out the job processing time at each of the given workstation. As the example of open shop, we have the car repair shops which has no specified routing (Ahmadian et al., 2021).

1.2.2 Flow shop scheduling

Another class of scheduling problem is Flow Shop, where a workshop assigned with a set of jobs and appropriate sequencing for processing on a set of machines or with other orders processing compliant resources. The purpose it to maintain a continuous processing of task with minimum of waiting and idle time. Every job has to process each job exactly once. The routing for this class is similar, all of the jobs have to visit machines with the same manner (Öztop et al., 2020).

1.2.3 Job shop scheduling

A problem related to the optimization where the resources get assigned the idea jobs with particular times with random scheduling.

Those manufacturing shops where a particular processing setup is followed, known as Flow Shops. These shops can't revisit any previous machines with respect to any type of processing. On the other hand, those manufacturing shops where any processing setup can be followed in a non-linear fashion and these shops can be revisited for processing are termed as Job Shops (Arikati, 2017), shown in figure 1-2.

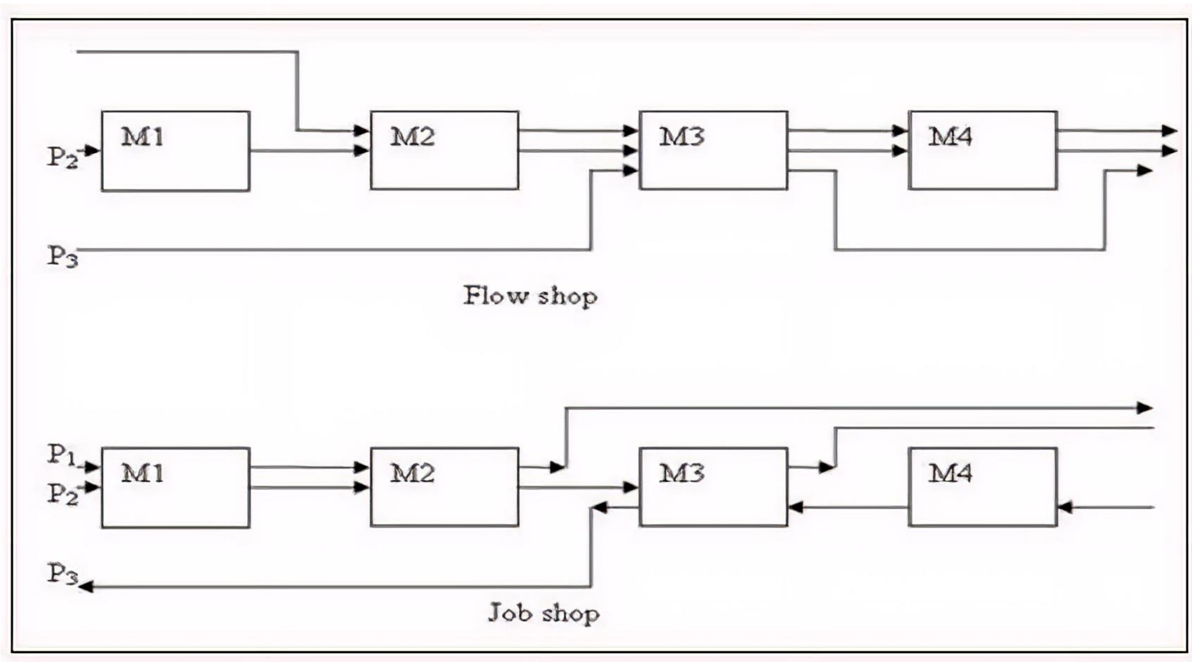

Figure 1.2 Flow Shop and Job Shop (Arikati, 2017)

1.2.4 Group Technology

Group technology (GT) is a technique by which manufacturing of parts take place, these parts are parallel with the manufacturing process, geometry, and the manufactured functions in a location by the implementation of minor number of processes or machines. The facilities are trying to fulfill all the needs of customer satisfactory, especially with a non-usual specific product. As per the requirement of effective customization strategy's implementation, the reconfiguration of the shopfloor is necessary to meet the customer's requirement on time with low cost. For this purpose, the group technology may be implemented which simplifies the flow of material create products and machine groups (Ham et al., 2012). For instance, the manufacturing facility is producing 15,000 various parts that may be arranged into 35-to-45-

part families. A series of machines are required in order to process all members of part family which leads to an efficient manufacturing method. This series of machines is termed as GT Cells, and the method is known as Cellular Manufacturing.

Part Family:

Part family is the group of parts with similar manufacturing properties and similar design. Parts are different in a part family while the resemblance are quite enough to do their classification as a family member. Different methods are utilized for the grouping of part family are:

1.3 Visual inspection

The Following image showing in the "before" diagram, the product families are moving in one direction towards the next process, while in the "after" diagram, the product families are moving in a different, more precise operation series to improve the waste and reduce the quality (TEIM, 2010).

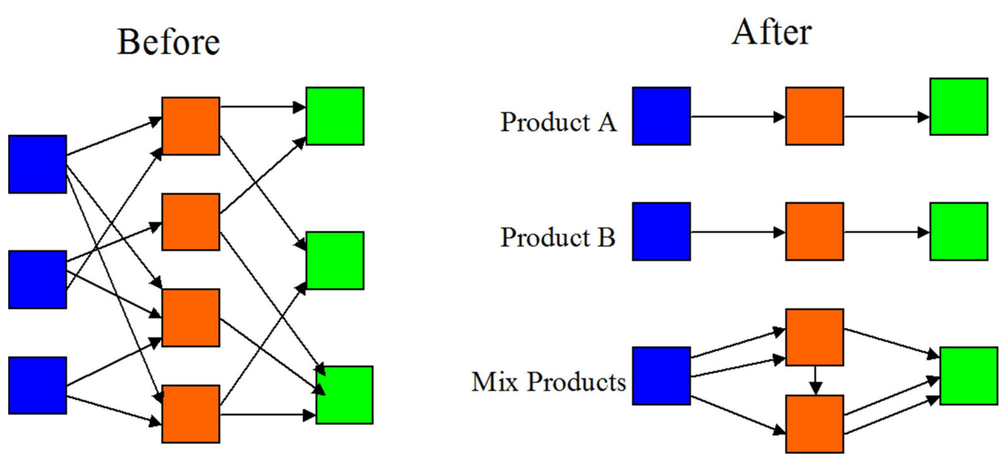

Figure 1.3 Selection of Family Parts (TEIM, 2010)

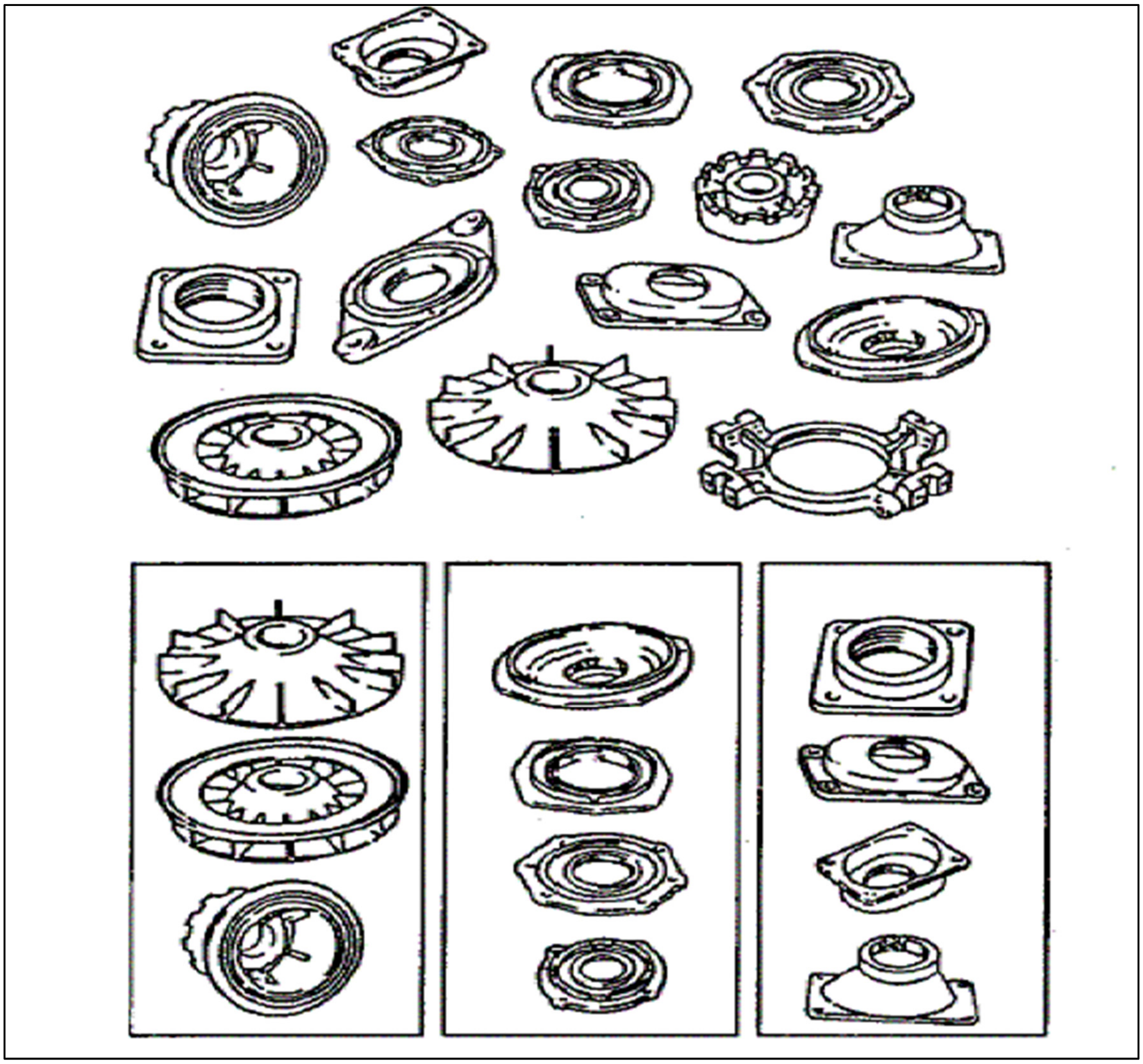

Figure 1.4 Group technology selection (Hyer and Wemmerlov, 2002)

1.4 Product Flow Analysis

The techniques used for analyzing of sequence routing when the parts moving through the fabrication, this technique is termed as Production flow analysis. Those parts having common routings are gathered into part families. In the same manner, those machines that are utilized to perform these routings can be gathered as a cell. This technique has been used by (Burbidge, 1991) in facility layout.

1.4.1 GT Advantages

- Scrap Reduction
- Lesser Time for Lead
- Provide Maximum Output
- Lesser Time for Setting-up
- Reduced handling of material

1.4.2 Cellular Manufacturing

Cellular manufacturing is a part of ‘lean manufacturing system,’ this model is based on the GT which provides full advantages of parts similarity by common processing and standardization. As far as functional manufacturing concerns, the similar machines are combined together. The functional layout is quite vigorous to the breakdown of machines, it has common fixtures & jigs, and support higher demarcation. In cellular manufacturing model, machineries are gathered as per the parts produced families. One of the major advantages is the significantly improved material flow which reduces the inventory, travelling distance, and cumulative lead times. Cellular manufacturing reduces the number of steps and provides to the workers to do multi-processing, multi-functionality, multiple processes operations, waste reduction, quality improvements, and simple maintenance of machine. This assists the workers to balance themselves while the lead time of the cell reducing, which results in the production of high-quality products with low cost on time by the companies. The purpose of cellular manufacturing is to provide flexibility in order to produce different low demand products with high productivity on large scale production. This modularity can be achieved by the cell designers in both process and product design. These cells are arranged with the U-shape shape, in result start and completion of the material flow within the cell will remain near to each other. This gives the fast task rebalancing without the station redesign because workers can cross the aisle, as it showed in fig 1.5.

1.4.3 Advantages of CMS

- Reduction in setup time. ...
- Reduction in work in progress. ...
- Reduction in material handling cost and time. ...
- Reduction in material flow distance. ...
- Improvement in machine utilization. ...
- Reduction in production lead time. ...
- Improvement in quality. ...
- Better worker morale.

In this Job Shop Sequencing example, the first worker is assigned with the jobs at machines 1, 2, and 10. The second worker is assigned to work with the machine 3, 4, 8, and 9, while the last worker assigned to work with the machine 5, 6, and 7 (PAC, 2012).

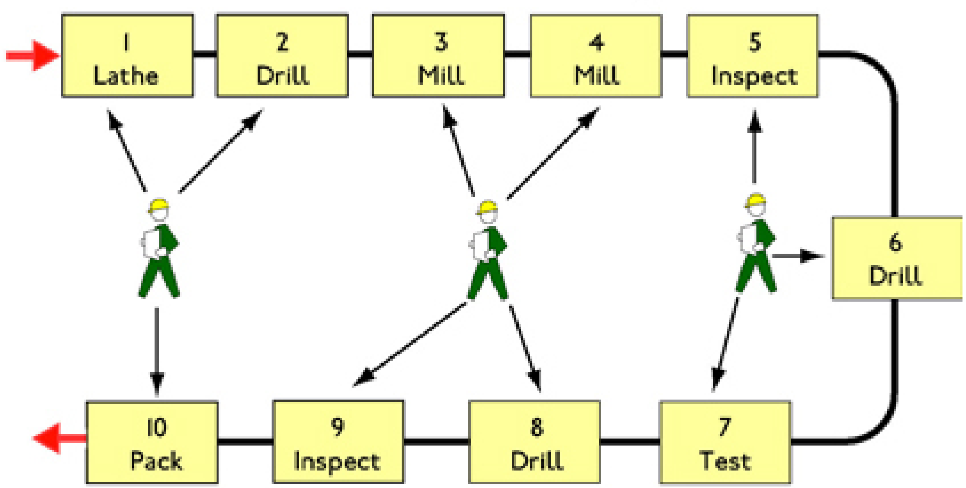

Figure 1.5 Job Shop Sequencing (PAC, 2012)

1.4.4 Job scheduling & job sequencing

The process in which the different tasks allocate system resources by an operating system, known as Job scheduling, while the process in which the jobs running order on a machine is called Job sequencing. Short term plans, named as operations schedules, are designed and implemented to the operational and sales plan. Many jobs must process frequently on one or more workstations and various tasks can be accomplished at each of the workstations. There can be the development waiting lines if the schedules not planned successfully to evade bottlenecks. Following are some common Sequencing Rules:

- “First Come First Served” (FCFP): “Jobs processed in the order they come to the shop.”
- “Short Processing Time” (SPT): “Jobs with the shortest processing time are scheduled first.”
- “Earliest Due Date” (EDD): “Earliest due date. Jobs are sequenced according to their due dates.”
- Critical Ratio (CR): “The ratio of processing time of the job and remaining time until the due date.”
- “Slack per Remaining Operations” (SPRO): “Slack per remaining operations (SPRO) due date and the total shop time remaining, including that of the operation being scheduled.”

In the following diagram, the job sequencing is visually described. The raw material of six types is shown on the left-hand side, while the final product is shown on the right-hand side. Each of the final products and the raw material is specified with a color. And arrows with the same color is showing the movement of raw material to machines in square shape. The movement of colored lines/arrows is showing the job shop sequencing and describing the transformation of raw material to the final product with a particular sequence.

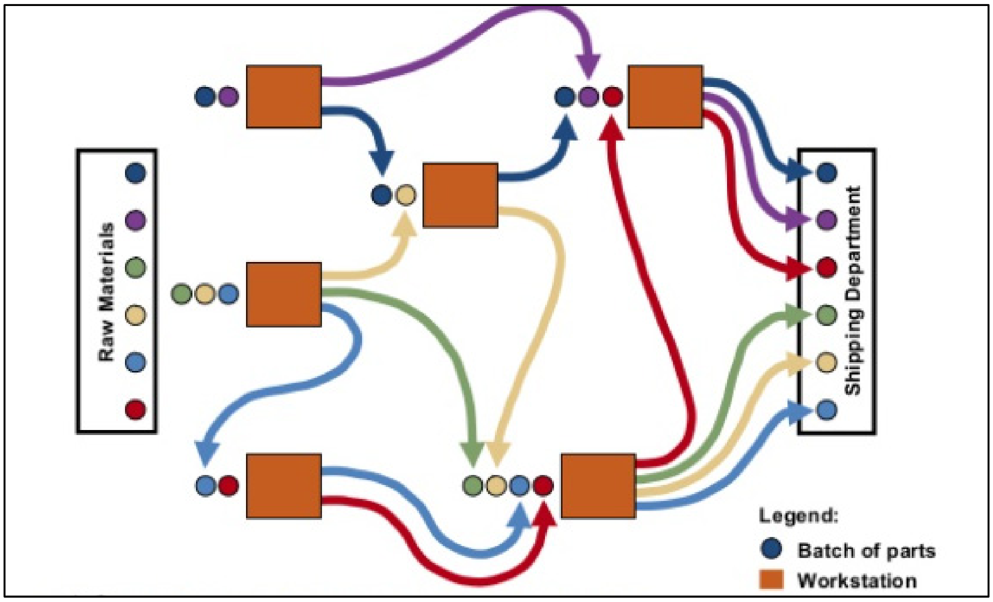

Figure 1.6 Job Shop Sequencing (Calmels, 2019)

1.4.5 Scheduling Optimization

A method is under research with the highest attainable performance and most economical within the certain constraints by minimizing undesired factors and maximizing desired factors. The maximizing is representing to try and gain the highest outcome without higher expense. Lack of time and full information is restricting the practice of optimization. The computer based simulation for the business problems, linear programming technique is used to gain the optimization.

There are two optimization methods in manufacturing systems:

- Production process
- Layout facility

1.4.6 Scheduling performance measurement tools

The numbers and the units are used to measure the performance and act as measurement tools. The number it is explaining the magnitude while its unit is telling about the meaning of number. The measurement of performance is coupled to a target. In terms of the manufacturing system is being used, such as maximizing profit & minimizing cost, completion time, flow time, lateness, total inventory, utilization, weighted flow time, tardiness, and Makespan. The measures of performance are interrelated to each other. Such as, the increase in use tends to decrease in the time for average flow. Similarly for a group of jobs, the reduction in makespan tends to the increment in the utilization. The understanding of the interaction between utilization, past due, makespan, and flow time can simplifies the section of good schedules.

1.5 The key tools

Makespan is "the total amount of time required to complete a group of jobs. Minimizing makespan supports the competitive priorities of cost and time"(Krajewski, 2007). Also, it means Minimizing makespan is the process to obtain the shortest schedule.

Makespan is denoted by M_{sj}

$$M_{sj} = T - S \tag{1}$$

T = *completion time of the last job i in the group.*

S = *start time of the first job i in the group.*

Total inventory is "a performance measure that is used to measure the effectiveness of schedules for manufacturing processes. The sum of scheduled receipts and on-hand inventories is the total inventory" (Krajewski, 2007).

$$TI = S_{all} - I \tag{2}$$

Where;

TI = "Total inventory"

S_{all} = "Scheduled receipts for all items"

I = "On-hand inventories of all items minimizing total inventory supports the competitive priority of cost."

Utilization is "the degree to which equipment, space, or the workforce is currently being used, measured as the ratio of the average output rate to maximum capacity. Maximizing the utilization of a process supports the competitive priority of cost (slack capacity)" (Krajewski, 2007).

Flow time is “the average time that a unit requires to flow through the process from the entry point to the exit point. Flow time is also known as throughput time or lead time” (Krajewski, 2007).

$$FT = CT + TJ \tag{3}$$

Where,

FT = Flow Time

CT = Completion Time

TJ = “Time since the job arrived at the workstation.”

Lateness is defined as completion time mines due date.

$$L = C - D \tag{4}$$

Where,

L = Lateness

C = Completion

D = Due Time

Tardiness is equal to:

$$T = \max(0, C - d) \tag{5}$$

Example of how to calculate the performance measures:

“The machine shop has five unprocessed jobs (J1, J2, J3, J4, and J5) numbers by the order they entered the Bottleneck machines queue” (Krishna, n.d.)

Table 1.1 Input data

Job #	Processing time	Due date
1	11	61
2	29	45
3	31	31
4	1	33
5	2	32

Table 1.2 Using first come first server

Sequence	Completion time	Due date	Tardiness
J1	11	61	0
J2	40	45	0
J3	71	31	40
J4	72	33	39
J5	74	32	42
Total	**268**		**121**

Mean Flow Time: (268) /5 = 53.4., ∑ L = 66. Number of Tardy Jobs: 3. ∑ T = 121

Table 1.3 Using shortest processing time

Sequence	Completion time	Due date	Tardiness
J4	1	33	0
J5	3	32	0
J1	14	61	0
J2	43	45	0
J3	74	31	43
Total	**135**		**43**

Mean Flow Time: (135) /5 = 27., ∑ L = - 67., Number of Tardy: 1., ∑ T = 43

Table 1.4 Using earliest due date

Sequence	Completion time	Due date	Tardiness
J3	31	31	0
J4	33	32	1
J5	34	33	1
J2	63	45	18
J1	74	61	13
Total	**235**		**33**

Mean Flow Time: (235) /5 = 47., ∑ L = 33., Number of Tardy: 4., ∑ T = 33

1.6 Meta-heuristic

1.6.1 Definition

"A meta-heuristic is formally defined as an iterative generation process which guides a subordinate heuristic by combining intelligently different concepts for exploring and exploiting the search space; learning strategies are used to structure information in order to find efficiently near-optimal solutions (Voß, 2009)." In other words, "A meta-heuristic is a set of concepts that can be used to define heuristic methods that can be applied to a wide set of different problems. In other words, a meta-heuristic can be seen as a general algorithmic framework that can be applied to different optimization problems with relatively few modifications to make them adapted to a specific problem (Dorigo et al., 2004)."

1.6.2 History

"In less than a decade, many researchers have suggested diverse varieties of meta-heuristics in solving manufacturing scheduling and logistics problems. (Chang, Chen, Fan, et al., 2008) developed a genetic algorithm with artificial chromosomes for multi-objective flow-shop scheduling problems. In practical applications, the manufacturing scheduling and logistic problems usually have more than one objective like minimization of cost, minimization of total processing time, and maximization of quality. This type of problem is very difficult to solve by traditional approach due to the high complexity and large problem size. In recent research, (Chang & Chen, 2009) proposed a sub-population genetic algorithm II (SPGAII) for multi-objective combinatorial problems. In terms of a logistic problem, many researchers applied different types of solution approaches. (Kumar and Vannelli, 1986) proposed a logistics planning and inventory optimization using swarm intelligence: a third party perspective (C.-J. Liao et al., 2013)."

(Lin et al., 2009) “Formulated an integrated multistage logistics network model considering the direct shipment and direct delivery of logistics and inventory. In addition, the authors employed an extended priority-based encoding method, combining a local search (LS) technique and a new fuzzy logic control (FLC) to enhance the search ability of the hybrid evolutionary algorithm. (Shukla et al., 2013) proposed constraint-based simulated annealing (CBSA) approach to solve the disassembly scheduling problem. (Huang and Liao, 2008) proposed an ant colony optimization combined with tabuo search for the job shop scheduling problem. (Liao and Liao, 2008) developed an improved MILP (mixed-integer linear programming) model for a two-machine flow shop with batch processing machines. (Tseng and Liao, 2008a) proposed a particle swarm optimization algorithm for hybrid flow-shop scheduling with multiprocessor tasks. (Tseng and Liao, 2008b) also developed a discrete particle swarm optimization for a lot-streaming flow-shop scheduling problem. In terms of machine scheduling, (Chang et al., 2009) developed a hybrid genetic algorithm with dominance properties for single machine scheduling with dependent penalties to minimize the weighted sum of earliness and tardiness costs. (Chang, Chen, & Fan, 2008) also developed mining gene structures to inject artificial chromosomes for the genetic algorithm to solve the single machine scheduling problems. (Chang & Chen, 2011) proposed a genetic algorithm (GA) enhanced by dominance properties for single machine scheduling problems to minimize the sum of the job's setups and the cost of tardy or early jobs related to the common due date. (Chang et al., 2010) also proposed a novel genetic algorithm that is developed by generating artificial chromosomes with probability control to solve the machine scheduling problems. The evaporation concept is also employed to reduce the effect of past experience and to explore new alternative solutions. (Chen et al., 2009) developed a guided mimetic algorithm (MA) with probabilistic models which serve as a fitness surrogate in estimating the fitness of the new solution generated by a local search (C.-J. Liao et al., 2013)."

“(Pang, 2013) suggested a genetic algorithm-based heuristic for two machine no-wait flow-shop scheduling problems with class setup times, which minimizes the maximum lateness. The recommended method combined the concept of migration in GA so that the algorithm won't be trapped into local optima. (Chou, 2013) proposed a particle swarm optimization (PSO) with a cocktail decoding method for hybrid flow-shop scheduling problems with multiprocessor tasks. In the PSO, a variety of job sequences are generated using the PSO procedure in the first stage, and the cocktail decoding method is used to assign the jobs to machines in sequential stages. (Shukla et al., 2013) proposed a portfolio of different evolutionary (DE) algorithms to reduce the computational time taken to solve the logistics optimization problem considering stochastic demand and mobility allowance. (Zhang et al., 2013) proposed a hybrid artificial bee colony (ABC) algorithm for the job shop scheduling problem. (Liang et al., 2013) proposed a meta-heuristic for drilling operation scheduling in Taiwan PCB Industries. (T. W. Liao et al., 2013) suggested a simultaneous dock assignment and sequencing of inbound trucks under a fixed outbound truck schedule in multi-door cross-docking operations. (Thiruvady et al., 2013) offered a constraint-based ant colony optimization (ACO) for a shared resource-constrained scheduling problem (C.-J. Liao et al., 2013)."

1.6.3 Applications & classification of the technique

"The solution is sought over a discrete search space. An example problem is the travelling salesman problem where the search space of candidate solutions grows faster than exponentially as the size of the problem increases, which makes an exhaustive search for the optimal solution infeasible. Additionally, multidimensional combinatorial problems, including most design problems in engineering such as form-finding and behaviour-finding, suffer from the curse of dimensionality, which also makes them infeasible for exhaustive search or analytical methods (C.-J. Liao et al., 2013)."

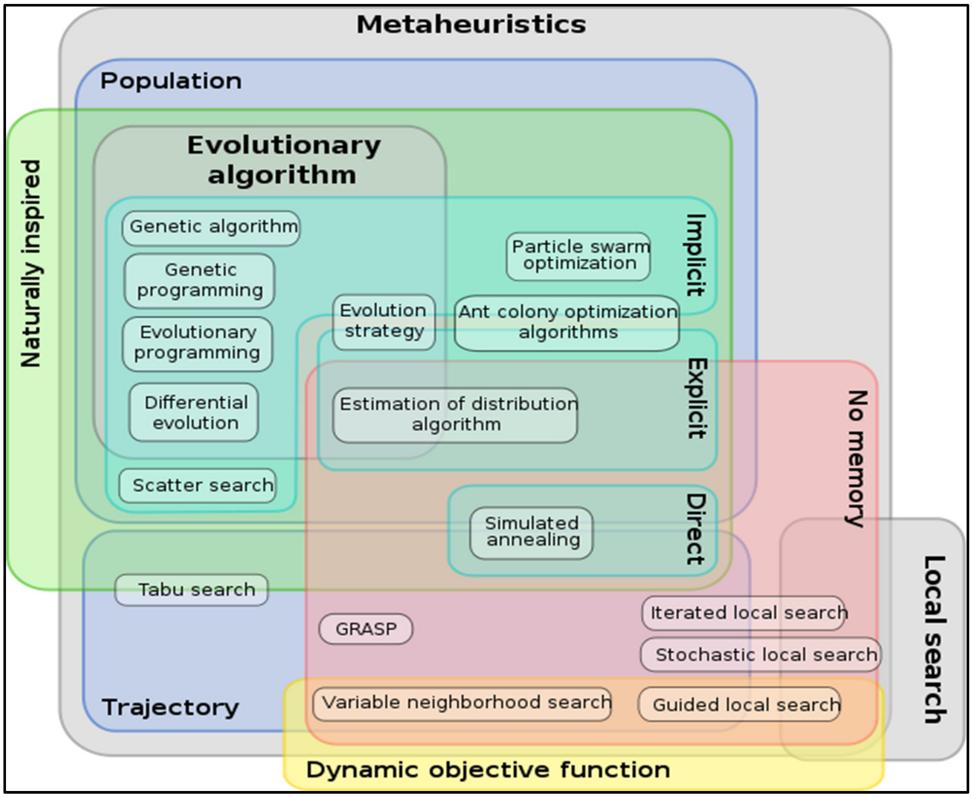

Figure 1.7 Classification of meta-heuristic (Balabanov et al., 2020)

1.7 Finding the best Meta-heuristics approach for the solution

It is like mission impossible to find the best metaheuristic approach to solve any scheduling optimization problem especially if the problem is NP-hard. Also, there are some elements have to be investigated prior to start such as the best Metaheuristic: is a higher-level procedure designed to find, generate and provide a sufficiently good solution to optimization problem. Limitations of search algorithms: it is related to continuous or discrete variables, design space, and accurately compute gradients of the solution. The chicken & egg problem: this is always debating which comes first yet the defined design space and characteristics of the design space are interfered. Robust solution: It is the solution we can obtain independently the choosing of starting point that mean ,with any starting point or initial solution, we can get always the same solution.

1.8 Solving methods

Scheduling job for cellular issues is certainly not an easy matter. Multiprocessor issue appears to be NP-Complete via partition polynomial issues. Production of the unit takes place in vigorous surroundings. The placement of an order is not predictable, and the assembly line should be adequately equipped for a quick and suitable response as and when desired to take up newer challenges. Hence, it is not possible to cover all bases and completely enumerate all angles in an issue. The manufacturing facility requires to be provided with a solution schedule in real-time, and therefore, the resolving methodology must be able to give a solution that is near-optimal in a short time span. Multiple solving procedures, inclusive of “genetic algorithms, search methods, neighbourhood relations, and Greedy approaches” objective to come up with viable solutions with varied outcomes for job scheduling problems.

Computational methods to give a feasible solution to a job scheduling problem by engaging heuristic hybridization and genetic search (Godinho Filho et al., 2014). A different type of technique applied was the multi-pass heuristic perspective amalgamated with genetic algorithms (Gonçalves et al., 2008). The salient features included were dispatching, initializing, evaluating, and loop consisting of selecting, pairing, mutilating, and reevaluating and substituting. This resulted in an even further lessening of time significantly. Another aspect of genetic algorithms offered for job scheduling issues with regards to launched and cut-off dates, with many criteria of tardiness and objective (Mattfeld and Bierwirth, 2004). Other priority rules, for example, FIFO, minimal procedural period, and critical ratio are applied for enhancing the decision process. An arrangement is evolved that categorizes any of the two procedures related to an issue. It was observed that the capacity of a GA diminishes with multiplying problem volume (Akhtar et al., 2019). Multi-stage decomposition assists in lessening the search space and the algorithm performance appreciably.

Sub-evolution and co-evolution were instigated in the GA to get to grips with job scheduling (Zhu et al., 2019). To provide an ideal time schedule and makespan criteria as a competency function of operation-related genetic algorithms, co-evolution was applied. Thereafter, furnishing a high assortment for the chromosome population, applying sub-evolution on total job time schedule limitations is the fitness function in GA. Softening of customary average and deviation of computed outcomes, this procedure manifests toughness at resolving job scheduling issues. One more genetic algorithm incorporated with meta-heuristic based on data mining was suggested to resolve job scheduling issues (Harrath et al., 2002). The modified genetic algorithm provides a learning set of feasibly applicable solutions, which were extracted through the "Learning Classifier System" (LCS). The extraction phase generates decisive rules duly modified to meta-heuristic, permitting for the methodical operation of schedule to machines. Fashioning the effectiveness of genetic algorithms, one research group suggested a "hybrid heuristic genetic algorithm" (Li and Gao, 2016). Rules of scheduling, like minimum possible processing time, also the number of activities to be performed, were incorporated into the process of genetic evolution. To enhance the execution of the solution, neighbourhood search approaches were embraced for another complementary practice. This modified hybrid genetic algorithm demonstrated very effectively and efficiently in contrast to the other prevailing procedures, inclusive of neighbourhood simulated annealing, search heuristic, and customary genetic algorithm. The procedure of the immune algorithm was suggested and is subjected to a series of lines of actions, consisting of antibody initialization, antigens initialization, evaluating, generating, and calculating (Liang et al., 2018). These binary strings congregate to a location where the appropriate value of the competency functions is established. Contrasting with the genetic algorithm, these suggested immune algorithm gives the solution at much speedier computation times.

A job scheduling procedure was scrutinized applying group limitations, meaning that the scheduled job to every manufacturing line is to be categorized and dealing jobs with similar practices are to be teamed (Chaudhry and Khan, 2016). The analytical study encompassed high-speed creation for a primary viable methodology through an examination of job flexibility in accordance with a predominant level of a comprehensive plan. The enhancement rules were applied in conjunction with a tabu search; the overall effect was the enhancement of overall evaluation and definite success.

In order to solve the job scheduling problem, a stochastic strategy was developed (Çaliş and Bulkan, 2015). A tabu search suggested standardizing for acquiring a near-optimal option. The suggested method relies on a renewable "neighbourhood search." It focuses an eye on not only short-term details but also long-term details through tabu search. Two plans of action, intensification, and diversification are applied to resolve the issue appropriately in constraint polynomial time. One more searching approach is established by easing and thrusting the capacity limitations. Afterward, this approach is blended with a" fast tabu search algorithm." Outcomes from such techniques demonstrate that this perspective is extremely successful in enhancing the solution quality.

In light of the tree search method for scheduling jobs, a heuristic was evolved to lessen the total weighted tardiness (Bierwirth and Kuhpfahl, 2017). Every task carries a particular cut-off date, and holdups results are penalized. “A schedule is set on by curtailing the optimum tardiness subject to allotted sub-schedules resolved at every junction of the search tree, and the successor junctions are initiated wherever the sub-schedule of the procedures is affixed. This results in obtaining the schedule at every junction, and a sub-optimum option is decided within the schedules obtained. Results demonstrated that in order to get the sub-optimal solution of issues, it is required to provide the minimum to scheduling jobs” (Ahmadian et al., 2020).

An add-on of job scheduling issues was analyzed; job routings are instructed acyclic graphs enabling the system to represent segmented or incomplete orders of actions containing sets of optional subgraphs, each made up of multiple functions. “A genetic algorithm and a tabu search are applied as a heuristic, relying on subroutines generally in practice. Partial insertion of sets of practices is first applied to the heuristic into a partial schedule, while secondly, this enhances a schedule routing option that is fixed. The initial subroutine depends upon the clinical placement practice, and secondly, the subroutine is stereotyping the typical procedures for scheduling jobs. Outcomes clearly demonstrate and suggest such a blend gives the best possible solution for three open issues” (Jat and Yang, 2011).

For random job orders, non-determined processing times, and unforeseeable occurrences, an exercise was carried out and researched for the manufacturing process line, such as the breakdown of machines and other hiccups. A comprehensive multi-agent structure inclusive of Lagrange multipliers is applied that caters to scheduled jobs allocated to flexible manufacturing units (Mihoubi et al., 2020). This methodology incorporates real-time resolutions and foreseeable resolutions that may tackle multiple programming-related issues. It also caters to and merges earliness and tardiness through multi-agent scheduling procedures for workshops, in harmony with just-in-time manufacturing philosophy (Yazdani et al., 2017). It also distinguishes whether a single operation is pending or jobs with multiple operations are pending through the multi-agent scheduling method. Such a program outperforms all prevailing scheduling practices, as demonstrated by the results. Job scheduling was put into practice to ascertain that every job must process one task on a machine (Rahmani Hosseinabadi et al., 2019). The establishment of the lengthiest courses becomes the focal point of data processing. Heuristics are applied using neighbourhood interaction. Acquiring a neighbour, one arc of the lengthiest course is selected, which is then reversed for a guaranteed feasible schedule for these transition steps. By applying Simulated Annealing Logarithmic Cooling Schedules within the polynomial-time, the issue can be resolved.

In connection with the operational assignments to the apparatus and also the sequential operation, a greedy heuristic was evolved for flexible job scheduling problems (Bekkar et al., 2016). To begin with, the polynomial algorithm is the first job to be secured. The job is then combined with a second job with associated operations. These fusions are arranged in a "Gantt chart" in accordance with the most effective schedule. This exercise is ongoing until all jobs are shaped in an effectively applicable combination to acquire the best possible results on machines assigned for the production.

Implementing a heuristic scheme dependent on asymptotic excellence in expectation for job overlaps to unsecured shop (Das and Dash, 2014). The entire theme is aimed at scheduling practices and applications to the side-by-side job processing as an option. The purpose provides the best possible schedule output and, at the same time, lessening the aggregate of job completion time (Khalid et al., 2019). With regard to the manner in which heuristic orders, the job is solely based on the average processing time of the operation. Also, a minimal bound regarding the optimal expense is also put in place. This is applied to manifest asymptotic optimality, probably when the process times are individualistic and similarly administered from whichever distribution with a definite deviation of the heuristic (Cortez and Costa, 2015).

Job schedules are all favorable practices for solving issues such as Greedy algorithms, search procedures, neighbourhood interactions, and greedy techniques. Though there are no sureties that it will be satisfactorily beneficial in tackling and achieving the objectives towards the near-optimal option to an NP-Complete within a stipulated timeframe for applying to such manufacturing surroundings (Subhaa et al., 2019). However, the study enables us to come up with a viable option that can be used as the basis for mathematical replicas for cellular job scheduling issues.
The heuristic will be beneficial to structure the replicas for an effectively appropriate problem-solving program and, at the same time, perpetuate a sustainable magnitude of optimality. The results will enable us to grasp a number of features of the mathematical replica in addition to selected attributes to the cells and jobs to the issues of scheduling for enhancing the effectiveness of problem-solving of the cellular job shop scheduling issue.

The following three chapters reveal the literature applications and the advantages of the Cellular manufacturing system, which is considered as a tool of lean manufacturing. Also, the chapters will discuss the adoption of the cellular manufacturing system using different metaheuristics algorithms, yet aiming to achieve one goal, eventually minimizing the completion work time (makespan). Due to the fact that various aspects of the cellular manufacturing system are a powerful tool for parts industries, a number of organizations are implementing this tool rapidly.

Therefore, in this thesis, a meta-heuristic algorithm called RC-filter was adopted in the cellular manufacturing system with the aim of reducing the production time (makespan) for two chapters, including hybrid metaheuristics and the last chapter a simulated annealing algorithm was applied for the same objective. Eventually, the obtained results of the three techniques in the three chapters were outstanding and outperformed all other metaheuristics from previous studies even benchmarked. These three experiments were in detail discussed, tested, and validated.

1.9 Discussion on the research gaps

Throughout many studies and research which has been done in this particular problem of scheduling optimization, there would always be a gap that leads to a new investigation by a potential candidate to find out either the difference or the similarity. Moreover, the gap is well known as which remains to be done or understood in the area of science. Nonetheless, the gap in this study is to minimize the makespan by using different metaheuristics in comparison. The three metaheuristics that have been used were SVS-algorithm, EGD & RC-filter in part one and part two of this study.

1.9.1 Issues in the techniques

The issue with the scheduling problems is that they belong to the NP-Complete complexity class. It is not possible to explore every possible feasible solution but only the easiest problem sets. The mathematical models help to represent the cellular job schedule issues. The integer linear problems help in the solution of job schedules. Due to the dynamic nature of manufacturing processes, the job schedule should be recognized in real-time. As the size is huge and the problem is complex, given by the mathematical modelling, it is not easy for the integer linear program to even find a solution that is feasible. The optimal solution for any manufacturing facility in such a case is not possible in a reasonable time frame.

The major aim of the scheduling is efficient resource allocation so that the maximum number of tasks can be completed cost-effectively within the hard and soft limits. In other words, the scheduling problem can also be seen as an optimization problem where the ultimate goal is to sort out the best schedule. Among these schedule optimization problems, the job shop scheduling problem (JSSP) is the most difficult one. It is deployed in the industry in many places, and it incorporates many scheduling issues that are faced in real life. The complexity of the JSSP problem increases with the increase in the number of imposed constraints and the size of the search space. The JSSP is an NP-hard problem, except for a few exceptions.

1.9.2 Job shop scheduling problem (JSSP)

Currently, many JSSPs incorporate a remarkable number of jobs and machines. They also include additional flexibilities and constraints. These scenarios cause a further increase in the complexity of the JSSP. The exact techniques, like dynamic programming or the branch-and-bound, are computationally expensive for searching the optimum solution for scheduling in a large search space. Therefore, it is far better to search for a near-optimal solution instead of an exact solution.

1.9.3 Evolutionary algorithms (EAs)

Probabilistic search techniques like Evolutionary algorithms (EA) can be used effectively to search for such solutions. These algorithms search and grow from a pool of solutions instead of searching for a single solution. They are found to be very robust and powerful for the solution of various singular and multiple objective problems. Many types of scheduling issues have been researched over time, and many different techniques have been designed for their solutions. But most of the research on scheduling problems has been for the single objective and the makespan optimization. But it should be kept in mind that most of the real-life practical scenarios are multi-objective, and they need multiple criteria to be considered by the decision-maker to reach any optimal conclusion.

1.9.4 Multi-criteria techniques

Any solution that is optimal according to any certain criteria only may turn out to be poor for the scenario where some other criteria are dominant. Hence the trade-offs that are required for considering several criteria help to provide meaningful insights to the decision-makers. But the multi-criteria research has been very rare as compared to single-criteria solutions for scheduling. There is very less work on tackling the multi-objective JSSP. The aim of the multi-objective JSSP is to look for multiple unique potential schedules, which are all near-optimal and are not dominated by some specific objective. Some of the performance measures used commonly in this area such as makespan, mean tardiness, and mean flow time. The makespan is the time required for the maximum completion of all the jobs. The mean flow time is the average flow time of the jobs, and the tardiness is the average of all the tardiness of all the included jobs.

The authors (Kim and Lee, 1994) deployed a “heuristic hybridization and genetic search as a technique to find a feasible solution for job scheduling.” Another technique deployed a genetic algorithm combined with a multi-pass heuristic approach as given in (Patkai and Torvinen, 1999). “The process steps included initialization, dispatch, evaluation, and a loop afterward, which contains the steps of selection, mating, mutating re-evaluation, and replacement. It was shown that computational time reduced a lot” (Patkai and Torvinen, 1999). The genetic algorithm proposed in (Mattfeld and Bierwirth, 2004) for “job scheduling included the release and due dates with multiple tardiness criteria as aims.” In this study, “different priority rules like first in, first out, critical ratio, and shortest process time are used in the decision process. A permutation was developed for prioritizing any two-operation involved in the scheduling problems. A decrease in the capabilities of genetic algorithms was found with an increase in the problem size”(Mattfeld and Bierwirth, 2004). "The search space is minimized, and the working of the genetic problem is improved by taking help from a multi-stage decomposition. In order to tackle job scheduling efficiently, co-evolution and sub-evolution processes were incorporated into a genetic algorithm” (Tsujimura et al., 2000). The co-evolution helped in operation-based genetic algorithms for providing the makespan and the idle time schedule criteria as the fitness functions. Consequently, sub evolution was deployed to provide a diverse chromosome population. In this case the total job waiting time is the fitness function for constraining the time schedule. The technique depicts robustness, insensitivity to disturbance of unforeseen shop floor, while solving the job scheduling issues with the alterations to average computational results and the standard deviation. Another “genetic algorithm and data mining-based metaheuristic” was developed by (Harrath et al., 2002) for the solution of the scheduling problems. The algorithm yields a “learning population of possible feasible solutions, which are mined by using the mean of classifier systems.” Decision rules are produced by the mining step that is converted into the meta-heuristic, which allows the efficient scheduling of operations. In order to “further boost the efficiency of genetic algorithms, a hybrid heuristic genetic algorithm was proposed" (Chen et al., 2011). The shortest processing time and most work remaining were combined with the genetic evolution process as scheduling rules. In order to improve the performance of the solution, the neighbourhood search method was deployed as a supplementary procedure. The developed algorithm was shown to be efficient and effective as compared to the other techniques like simulated annealing, the neighbourhood search heuristic, and the conventional genetic algorithms. An immune algorithm technique was developed in (Miyashita 2003) that deploys multiple steps, which include "initialization of antibodies, antigens, the evaluation, generation, and calculation. The binary strings will collect at a point where an optimal value of the fitness function is realized. As compared with the genetic algorithms, these proposed immune algorithms give solutions quickly, and lesser time is needed for the computation" (Miyashita 2003). A group constraint-based job scheduling technique was researched in (Ohmae et al., 2003), where the aim is that the schedule for an individual line is pre-decided and the jobs following the same process should be grouped together. The technique rapidly generates an initial viable solution by the analysis of job flexibility that influence the whole procedure. The total evaluation was improved and the effectiveness was confirmed as a result of combining the improvement rules with tabu search.

A stochastic strategy was developed in (Ai-Hua Yin and Wen-Qi Huang, 2002) for the solution of the scheduling problems. A tabu search was developed and carried out in order to find a near-optimal solution. The technique is based on a repetitive "neighbourhood search." This strategy keeps information on both short-term and long-term information. In order to efficiently solve the issues in polynomial time, the two techniques named diversification and intensification are deployed. The authors (Yunpeng Pan and Leyuan Shi, 2005) developed a technique that is based on "relaxing, and then the capacity constraint is imposed. Consequently, this technique is merged into the fast tabu search algorithm. The results show the effectiveness of this technique as it improves a range of test issues." Another heuristic was proposed in (Asano and Ohta, 2002), which was based on "a tree search procedure for scheduling the jobs and aiming at minimizing total weighted tardiness." Every job has a due date assigned and carries a delayed penalty as well. The schedule is calculated by "minimizing the maximum tardiness focused at determined sub-schedules, which are solved at every node of the search tree, and the successor nodes are created. The schedules of operations are fixed at each node at the successor nodes. Hence, a schedule is determined at each node, and a near-optimal solution is generated from the generated schedules. The results show that the algorithm is capable of finding a near-optimal solution with very little time" (Asano and Ohta, 2002). The authors (Kis, 2003) developed an extension of the previous technique, where the job routings are treated as acyclic graphs;. These graphs help in modeling the partial orders of operations. It contains the sets of substitute sub graphs which contain several operations for each of them. The heuristics used were a tabu search and a genetic algorithm which are based upon two common subroutines. The first subroutine attaches a set of operations into the partial schedule, and the second subroutine is an overview of regular techniques for job scheduling. The results depict that the technique provides the finest possible solution for the three open problems.

1.9.5 Overall shortcomings in the developed techniques

It is concluded that all of the approaches like genetic algorithms, neighbourhood relations, greedy methods, and search methods perform very well for efficient scheduling of jobs, but they do not guarantee to reach the near-optimal solution for any NP- problem in a realistic time frame that can be used in dynamic manufacturing techniques.

CHAPTER 2

METHODOLOGY FRAMEWORK

2.1 Proposed Methodology Framework

In the first part of this thesis, a new metaheuristic algorithm called Resistor Capacitor filter (RC-filter) was applied to optimize the NP-hard problem in the cellular manufacturing system. This algorithm had been used by Nabil & Mustapha in the flow shop problem (Nahas and Nourelfath, 2014). Not only has it proven its efficiency, but also it has outperformed the other techniques. The first strong point of using this very powerful optimization algorithm is to obtain good results within a reasonable running time. The second point is the technique used to determine exceptional elements. These two jobs were optimized at the same time as the cellular manufacturing system. Simply, the RC-Filter approach was applied with the aim of determining the best sequence of parts, which would minimize the makespan.

In the second part of this thesis, two metaheuristics set together as a hybrid tool, RC-filter & EGD, were designed to resolve the NP-hard problem optimization. The EGD approach was used previously by Ben Mosbah & Dao. The SVS algorithms were used by M. Solimanpur et al. The result of the hybrid approach compared with results from the previous studies individually RC-filter, EGD & SVS algorithms. The hybrid metaheuristics approach was implemented to find out a great solution in a reasonable running time. Moreover, the technique was used to tackle the myriad of the exceptional elements, hence tested and validated using several problems. The obtained results by the hybrid metaheuristics approach were compared with different methods used in the literature. The Flowchart of the proposed RC-Filter_EGD approach is shown in Fig. 2.10.

In the third part of this thesis, an approach was proposed called simulated annealing meta-heuristic algorithm. This approach was used by many researchers in different fields. The obtained results were compared with three other metaheuristics that were used in previous studies. The goal is to reach the best sequence of parts, thus, obtaining the minimum makespan.

The work of this experiment has two stages that are analyzed in this work; each stage has two parts:

- Stage1 part 1: using the original architecture of the cells, the exceptional elements were optimized by the simulated annealing. The original cells were optimized as a job shop problem because there were a lot of inter-cell movements;
- Stage1 part 2: in this part, the sequence in each cell was optimized. The first stage, characterized by these two parts, represented the first stage of this work with the aim of reducing the inter-cell movements used in a dynamic cell environment.

In the second stage of this work, a dynamic manufacturing cell was used. This stage is comprised of two parts:

- Stage2 part1: in this part, new cells were designed using exceptional elements only. To do this task, the required machines used for the manufacturing of exceptional elements were moved to other cells. A specific cell's architecture was designed to handle exceptional elements. The aim of this part was to give a minimum of inter-cell movements and handling;
- Stage2 part 2: in this part, the configuration of the original cells was used, and the sequences of the parts were optimized in each cell. The optimization of the sequence of the parts was determined via the simulated annealing algorithm.

2.2 Thesis organization and our contributions

The work included in this thesis was the subject of three peer-review journal papers, and the second paper was accepted at IEEE 2017 conference. The writer was the main author in all papers. Two of these journal papers have been published. Chapters 3 to 5 represent the three journal papers topic of this research. Prof. Thien-My Dao supervised the realization and validation of all of the research work. He was a co-author of every paper.

2.2.1 First journal paper

In chapter 3, the first paper entitled ‘’ Optimization of production scheduling with RC-Filter approach: A case study’’ is presented. This paper was published in the ‘’*International Journal* *of Applied Engineering Research*'' in November 2018. A metaheuristic approach was used to optimize the sequence of parts, including exceptional elements with the aim of minimizing the makespan. This paper proposes a methodology based on the RC-Filter algorithm. The proposed approach helps to determine the optimal sequences of parts with exceptional elements in a few running times. The proposed methodology was validated using a case study and several problems selected from the literature. This paper contributes as the first time used RC-Filter algorithm in cellular manufacturing system and approved its efficiency.

Summary of the paper

The "cellular lean manufacturing system" (CMS) is a great model for the manufacturing industry; it reduces the processing steps, cost and simplifies the planning of production. By using the CMS, there are excellent manufacturing configurations in order to optimize schedule and perform the reduction in manufacturing Makespan. But during the scheduled optimization, it is quite difficult to reduce the Makespan; it is known as the "NP-hard problem." For this problem, a technique is generally utilized that performs reduction in Makespan, termed as Metaheuristic Algorithms. In this paper, the RC-Filter metaheuristic algorithm is used to reduce the Makespan time of manufacturing scheduling by providing the best sequence of parts. RC-filter consists of a resistor and capacitor-based filter that only pass low-frequency signals; it reduces the amplitude of the signals. This proposed approach is applied to the thirteen manufacturing scheduling problems obtained from the previous researches. A comparison is made between the number of cells used in those problems and the Makespan time obtained by the RC-Filter algorithm. The results of this experiment showed that 11 out of 13 problems improved their Makespan time after the implementation of the RC-Filter approach. On average, these problems were improved by 17% when compared to the previously used EGD algorithm. On the other hand, it is also noted there were ten problems that were previously used in the SVS approach; they show Makespan improvement of 44% after the implementation of the RC-Filter algorithm. Furthermore, in this paper, a case study is also used to check out the performance of the RC-Filter algorithm on a bigger problem. The selected cased study problem has 24 machines distributed into the seven cells to cause 40 parts. The selected manufacturing scheduling problem previously used the EGD algorithm technique. As the proposed RC-Filter algorithm approach was applied to the given big scheduling problem, their results showed an improvement of 4%. This confirms that the proposed approach is quite effective for both small and big manufacturing scheduling problems to improve the Makespan time. All the results of performed experimentation are mentioned in the form of tables, matrices, and Gantt charts.

2.2.2 Second journal paper

Chapter 4 presents the second paper, ‘‘Optimization of the cellular manufacturing scheduling using the RC-filter and EGD hybrid Meta-heuristics Approach’’ published in ‘‘*International Journal for Interactive Design and Manufacturing (IJIDeM)*’’ in June 2019. This paper describes an optimization algorithm that is able to give a great solution characterized by the best sequence of parts. The proposed tool also provides a solution to make exceptional elements where they are manufactured as soon as the intended machine is available. The proposed tool was hybridization between the RC-Filter and the EGD metaheuristic algorithms. The proposed tool was used to solve 13 problems of different sizes, and the obtained results were compared with that given by RC-Filter, EGD, and SVS-algorithm. This hybrid Meta-heuristics approach was the first time being used and contributed to the domain of scheduling optimization.

Summary of the paper

The Cellular Manufacturing System (CMS) is an important system for the manufacturing industry; it reduces the production time of the product, results in the manufacturing industry's ability to fulfill the increasing requirements of marketing. The Makespan should reduce by the optimization of the “cellular manufacturing system,” which is a very difficult task and classified as NP-hard. In order to overcome this problem, different metaheuristic algorithms were used by the previous researchers, and they got success but not sufficient. In this paper, a hybrid metaheuristic algorithm by using two different techniques, one is “RC-Filter,” and the other is the “Extended Great Deluge” algorithm. The idea behind this approach, the combination model of two heuristic algorithms, will provide the best manufacturing scheduling sequence and minimize the Makespan. The RC-Filter is consists of the resistor and capacitor filter, which filters the high amplitude of the signal. Previously, this technique is used by many researchers to the “flow-shop scheduling optimization” problems. On the other hand, the “Extended Great Deluge” (EGD) is also effectively used by many researchers in group scheduling optimization and manufacturing cell formation optimization. By the use of hybrid metaheuristic algorithms of RC-Filter and EGD techniques, we want to schedule the manufacturing cells along with the exceptional elements. These two best metaheuristic techniques provide the performance advantages when they work together, they provide the best sequence of parts, and the Makespan time will be reduced. The proposed hybrid RC-Filter & EGD approach has experimented on 13 different problems selected by the previous literature. The results of the Makespan of these problems from the previously used approaches, RC-Filter, EGD algorithm, and singing voice separation (SVS) algorithm, are individually compared with the proposed hybrid approach. The results showed an improvement of 71% in the ratio error percentage of makespan. In this paper, a case study also experiments with the proposed hybrid RC-Filter and EGD algorithm approach. The case study problem has eight machines that were grouped into three cells and make ten manufactured parts; there were also four exceptional parts that required outside cell operations. This problem was resolved by the previous researcher through the SVS algorithm approach; another researcher resolved this problem by using the EGD algorithm in order to solve the manufacturing cell scheduling problem. The results obtained by these two different approaches, optimal Makespan were obtained 78, and 56, by SVS and EGD, are compared by our proposed approach and found that the obtained makespan is equal to 50 where the improvement was 35.9 % over the SVS-algorithm and was 10.7% over the EGD algorithm.

2.2.3 Third journal paper

Chapter 5 presents ‘‘Optimization of production scheduling on combining a cellular environment and job shop manufacturing process using simulated annealing approach’’ which has been submitted Ain Shams Engineering Journal on Oct 30, 2020, https://www.journals.elsevier.com/ain-shams-engineering-journal.The proposed methodology was based on the SA algorithm to minimize the makespan by optimizing the sequences of the cells. The proposed approach was applied to a case study and 13 problems with several exceptional elements. Great results were obtained; in addition, the performance of the proposed tool was compared with RC-Filter, EGD, and SVS-algorithm.

Summary of the paper

The research paper aims to optimize the production schedule by combining the manufacturing cell movement and the exceptional elements together using the simulated annealing approach. Nowadays, companies require to reduce the production time for the better flow of the manufacturing organization to benefit more from the machines. In this research paper, a simulated annealing approach is used to solve the problem. Besides, different authors proposed different approaches to reducing the running time of the cell and inter-cells movement with the exceptional element manufacturing as well. Most of the techniques applied are heuristic and meta-heuristic. However, the latter is a better approach to solving these problems and provides accurate results. The reason for the metaheuristic approach is that they are easily adaptable to the environment and have fast solutions. They are mostly used in solving the combinatory problem. Simulated annealing (SA) is a metaheuristic technique. Its main purpose is to use the material with the least energy consumption or in its equilibrium state. To get this approach workable, the optimal sequence is considered for the manufacturing of the cells and exceptional elements. Furthermore, an iterative optimization process sequence was used to find out the optimal usage of the machines. Moreover, for the iterative optimization process, a methodology was proposed. The methodology clearly explains that there are two stages of manufacturing; the first part consists of accumulating the exceptional element (EE) parts together, first using the simulated annealing (SA) as before the EE was scattered in different manufacturing cells taking more time. The second part consists of the manufacturing of the rest of the parts that are without the exceptional element (EE) using the SA algorithm in each cell. The last part is the combining of the two stages according to the relevant machine available. The division of the sequencing reduced the time of the manufacturing process. This time reduction was calculated by (Sridhar and Rajendran, 1993) calculation method. Besides, the inter-cell movement is also decreased with this assembly technique using the simulated annealing (SA) approach. A case study has also been done to implement the following approach. MATLAB is used to implement the proposed tool. However, to validate the performance of the tool, we compared our results with different tools that are RC-Filter, EGD, SVS algorithm, and SA. The most authentic and reasonable results are obtained by the tool and approach we applied to optimize the scheduling of the production using the SA approach minimizing the makespan in each cell and each inter-cell movement as well. They are reliable, especially for large-size manufacturing production scheduling.

CHAPTER 3

OPTIMIZATION FOR PRODUCTION SCHEDULING WITH RC-FILTER APPROACH: A CASE STUDY

3.1 Abstract

Production scheduling is central to the factory's planning and control system. One of the attractive production scheduling systems is the cellular manufacturing system (CMS). The CMS is a structured system based on group theory. Several advantages of the CMS concept include the makespan principally and flow time reduction. The CMS is an NP-hard optimization problem. Depending on the size of the problem, the number of the machine, and the number of parts, the calculation time needed to get the optimal solution increases exponentially. To resolve NP-hard optimization problems, metaheuristic algorithms are the greatest solution to get good solutions in a reasonable time.

In this work, we propose a new methodology to optimize the sequence of parts in each manufacturing cell, including exceptional elements. This technique is based on the RC-Filter algorithm. The proposed methodology was used to optimize the sequence of parts, including exceptional elements to minimize the makespan. The proposed approach was validated using twelve problems taken from literature, and the results were compared with that given by the extended great deluge algorithm.

3.2 Introduction

The cellular lean manufacturing system (CMS) is a model for workplace architecture and became an integral part of lean manufacturing systems. The CMS allows machines and parts to be grouped in manufacturing cells. These cells are sharing the same required production process route, which means the parts are going to be processed on the same machines within the cell (Fletcher and Powell, 1963). The CMS has several advantages such as reducing the costs of the material handling, reducing the number of the processing setups undertaking, reducing the work in process inventories, simplified production planning & control, and also improving space utilization. Moreover, CMS provides a production infrastructure that facilitates the successful implementation of modern manufacturing technologies such as just-in-time manufacturing systems, flexible manufacturing systems, computer integrated manufacturing, computer-aided design system, etc.

The CMS is an excellent manufacturing configuration to optimize the scheduling and minimize the Makespan. The optimization process needed to get the minimum of makespan is a very hard & difficult task; it is considered an NP-hard problem; therefore, it has been widely known to use metaheuristics algorithms to solve this type of problem in reducing running time. In the last two decades, many metaheuristic approaches had been used by researchers in engineering, especially in scheduling. For instance, (Gaafar and Masoud, 2005a) found one type of search strategy is an improvement in simple local search algorithms; Metaheuristics of this type include simulated annealing, tabu search, iterated local search, variable neighbourhood search, and GRASP (Gaafar and Masoud, 2005b). Also, another type of search strategy has a learning component to the search, so this type includes ant colony optimization, evolutionary computation, and genetic algorithms (Kirkpatrick et al., 1983). Moreover, a great deal of the algorithms was developed for group scheduling problems, which usually have two stages. The first stage determines the sequence of parts within the cells, and the second stage determines the sequence of cells (Campbell et al., 1970). (Hitomi and Ham, 1976) define lower bound for the optimum Makespan and propose a branch and bound technique to determine the optimum sequence of parts and cells. Since the group scheduling problem is NP-hard (Logendran and Nudtasomboon, 1991) and several researchers have attempted to develop heuristics for the group scheduling problem. (Wemmerlov and Hyer, 1989) compared the performance of eight parts family scheduling procedures and reported that the family-based scheduling approaches perform superior with respect to minimum flow time and lateness. (Sridhar and Rajendran, 1996) Introduced a multi-objective model that minimizes the makespan and another performance measurement, yet their model was not able to tackle some exceptional elements that visited other cells.

(Solimanpur et al., 2004) presented a heuristic called the SVS-algorithm to minimize the makespan within cell scheduling, including exceptional elements (parts from other cells visiting another cell); nonetheless, one of its disadvantages is that not prioritizing the order of the operations in terms of a high number of inter-cellular movements. The two stages of the SVS algorithm are Intra-cell scheduling and inter-cell scheduling, which does determine not only the sequence parts in the group but also the sequence of cells. Kirkpatrick et al. primarily introduced the simulated annealing algorithm in order to solve hard combinatorial optimization problems. (Abdallah and Dao, 2011) developed a metaheuristic called Extended Great Deluge (EGD) to optimize the scheduling of manufacturing by minimizing the makespan and other performance measurements. The EGD algorithm was able to reduce the setup time of the machines and hence obtained outstanding results.

The optimization of scheduling in a manufacturing environment is aimed to minimize the makespan or to minimize the total production time. This type of problem was classified NP-hard, where the calculation time increase exponentially depending on the size of the problem. For this reason, researchers tried to develop techniques, especially meta-heuristics, which give results in reasonable running time. (Sridhar and Rajendran, 1993) proposed a model to minimize the makespan, the flow time, and the idle time in the cell and without introducing the exceptional elements. (Abdallah and Dao, 2011) developed a model to minimize the makespan and the flowtime in a cell manufacturing environment, including the exceptional elements, the proposed model was based on an extended great deluge algorithm. A model based on ant colony optimization proposed by (Guo et al., 2012) was applied to determine the great sequence of parts in complex Job-shop problems. A methodology was proposed by (Bilyk et al., 2014) to solve parallel machine scheduling problems.

In this study, we are interested in the manufacturing cell problems, including exceptional elements. In the aim to solve this problem, we proposed a hybrid approach based on two metaheuristic algorithms. The first one was the RC-Filter algorithm developed by (Nahas and Nourelfath, 2014), and the second one was the Extended Great Deluge algorithm introduced by (McCollum et al., 2009). Given the importance of this problem, many resolution methods have been developed in the scheduling optimization field. Therefore, in this paper, a new metaheuristics algorithm called Resistor Capacitor filter (RC-Filter) will be applied to tackle the scheduling optimization problem in the cellular manufacturing systems.

3.3 Methodology

The proposed methodology was based on a meta-heuristic algorithm. The used metaheuristic algorithm is called the RC-Filter. This approach was applied with the aim to determine the best sequence of parts that minimizes the makespan.

3.3.1 RC-Filter algorithm

The proposed metaheuristic algorithm was introduced by (Nahas and Nourelfath, 2014)in the flow-shop scheduling optimization domain. RC-Filter is considered as one of the low-pass filters, which consists of a resistor (R) in series with a capacitor (C). It allows passing only low-frequency signals. This operation is made by reducing the amplitude of signals with high frequencies. The low-pass filter can be designed in many different forms. For instance, electronic circuits or digital algorithms for smoothing sets of data, and more. The RC-filter algorithm steps, as described by (Nahas and Nourelfath, 2014), are as follows:

Initialization of parameters: β *and* β_0

Initialization of the maximum number of iteration N and the decreasing rate $\Delta\beta$

Select initial solution S_0 and set $S = S_0$

While the number of iteration is $< N$:

Randomly select a solution S* from the neighbourhood space

Calculate $G' = f(S) / f(S^*)$

Calculate $G = 1/\sqrt{1 + (\beta/\beta 0)^2}$

If one of the two conditions satisfied $G' \geq 1$ *or* $G(\beta) > G'$

Set $S = S^*$ and $\beta = \beta - \Delta\beta$

End while.

3.4 The proposed approach

In this study, we are interested in the scheduling of manufacturing cells, including the exceptional elements. To solve these complex problems, an approach based on the RC-Filter algorithm was proposed with the aim of getting the best sequence of parts that provides the minimum makespan. The Flowchart of the proposed RC-Filter approach is shown in Fig 3.1.

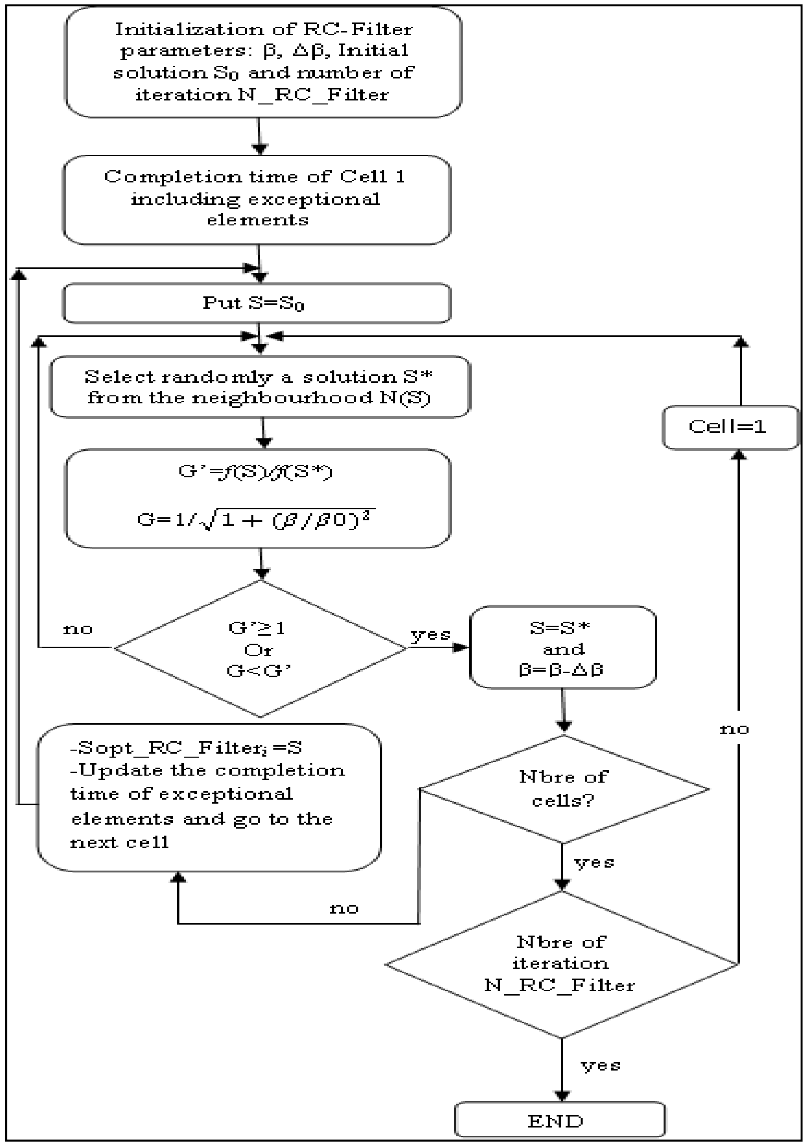

Figure 3.1 RC-Filter flow chart

The calculation of the makespan ($f_{(S)}$ in Fig. 3.1) was performed using the model proposed by (Sridhar and Rajendran, 1993); the proposed model is as follows:

n the number of jobs to be scheduled in the cell.

m the number of machines in the cell.

tji the processing time of job *j* on machine *i* .

s the set of jobs already scheduled.

$q(s, i)$ the completion time of the partial schedule

s on the machine i.

Fs the flow time of all jobs in s.

The formulation of the problem is:

Initialize $T=0$, $Fs=0$ and $Ms=0$

For $j=1$ to n do

$i = 1$ to m do

if $tji > 0$

then

compute the completion time $q(sj,i)$ of partial

schedule sj

$$q\ (sj,i)=\max[q(s,i);\ T]+tji \tag{3.1}$$

update

$$T = q(sj,\ i) \tag{3.2}$$

else

$$q(sj,i)= q(s,i) \tag{3.3}$$

the total flowtime of jobs in sj is:

$$Fsj = Fs + T \tag{3.4}$$

The makespan αsj of the partial schedule sj is:

$$Msj = \max\ (Ms\ ,\ T) \tag{3.5}$$

The objective function f is

$$f\mathrm{sj} = Msj$$

The optimization process of the hybrid approach proposed in this work is done as the following steps:

Initialization of the RC_Filter parameters: β, $\Delta\beta$, the initial solution S_0 and the number of iteration N_FC_Filter and give the completion time of the cell one, including exceptional elements.

Put $S=S_0$

Define the neighborhood N(S) and select randomly $S^* \epsilon$ N(S)

Calculate $G' = f_{(S)} / f_{(S^*)}$

Calculate $G=1/\sqrt{1+(\beta/\beta 0)^2}$

If $G' \geq 1$ *and* $G(\beta) > G'$ are not satisfied, go to step 3

If: $G' \geq 1$ *or* $G(\beta) > G'$

Put $S=S^*$ and decrease $\beta=\beta-\Delta\beta$

If the number of cells is not reached:

Put Sopt_RC_Filter=S

Update the completion time of exceptional elements and go to the next cell (Cell =Cell+1).

Go to step 2

If the number of cells is reached:

If the number of iteration < N_RC_Filter

Initiate the number of cells (Cell=1)

Go to step 3

If the number of iteration is reached:

Save the solution $Sopt_i$

END.

3.5 Computational results

In this section, we present an application of the proposed approach to different problems. The performance of the proposed approach was compared with the extended great deluge (EGD) algorithm and singing voice separation (SVS) algorithm.

3.6 Illustrative example

To illustrate the performance of the proposed methodology, this meta-heuristic approach was applied to the example shown in Table 3.1. The example is composed of ten parts manufactured using nine machines grouped in three cells. Table 3.1 showed the operation times of each part. In this example, they are five exceptional elements that require operations outside of their cells where they belong.

Part 1 is manufactured in cell one but is requires one operation on machine K in cell number 2 and one operation on machine G in cell number 3. Part 5 is manufactured in cell number 2 and requires two operations outside of cell 1, one operation on machine A and one operation on machine C in cell number 1. Part 7 is affected by cell number 2 but also required two operations on machines A and B in cell number 1. Part 8 and 9 required one operation on machine K and A, respectively, outside of their cell (cell 3).

The operation time was needed to calculate the makespan corresponding to the partial sequence. The idea was to add fictive parts and machines in the cells where the exceptional elements are realized. For example, parts 1, 2, 3, and 4 are manufactured on cell one but also to realize operations on parts 5, 7, and 9. These exceptional elements were added to the family of parts manufactured on cell 1. Fictive machines were added in cell 1; these machines were needed to realize exceptional elements of the part family affected to cells 2 and 3; in this case, we added fictive machines K and G in cell 1. This step helps to define the completion time of exceptional elements on part 1 with the aim to be used in the optimization process of the next part family (on cells 2 and 3). For each iteration, the optimization process was as the following steps:

Step 1: start with cell 1; the operation time on the cell one was presented in Table 3.1. The Gantt diagram of the initial solution is shown in Fig 3.2. The makespan in this cell is 50—the optimal sequence is given by the proposed method RC-Filter was**7-4-9-3-1-2-5.** The completion time of exceptional elements was calculated to update the operation time of cell two according to the optimal sequence (Table 3.2). The completion time of part 1 on machine K was 36 and was 43 on machine G.

Table 3.1 Operation time

		Parts									
		1	2	3	4	5	6	7	8	9	10
Cells	Machines										
Cell1	A	6	4	8	9	5		5		8	
	B	9	10		5			13			
	C	1	7	4		6					
Cell2	K	8				7	7	3	5		
	L					13	8	2			
Cell3	F								5	13	3
	G	7							15	8	6
	H								8	6	
	R								8	3	7

Table 3.2 Operation time for cell 1

		Parts						
Machines		1	2	3	4	5	7	9
Cell 1	A	6	4	8	9	5	5	8
	B	9	10	0	5	0	13	0
	C	1	7	4	0	6	0	0
	K	8	0	0	0	0	0	0
	G	7	0	0	0	0	0	0

Table 3.3 Completion time for cell 1

		Parts						
machines		7	1	3	5	2	4	9
Cell 1	A	5	11	19	24	28	37	45
	B	18	27	27	27	38	43	45
	C	18	28	32	38	45	45	45
	K	18	36	36	38	45	45	45
	G	18	43	43	43	45	45	45

According to the table 3.3, the completion time of part 5 on machine A and C were 24 and 38, respectively. The exceptional elements of part 7 on machines A and B were 5 and 18, respectively. Finally, the exceptional element of part 9 on machine A was done after 45 unit time, as shown in Table 3.3.

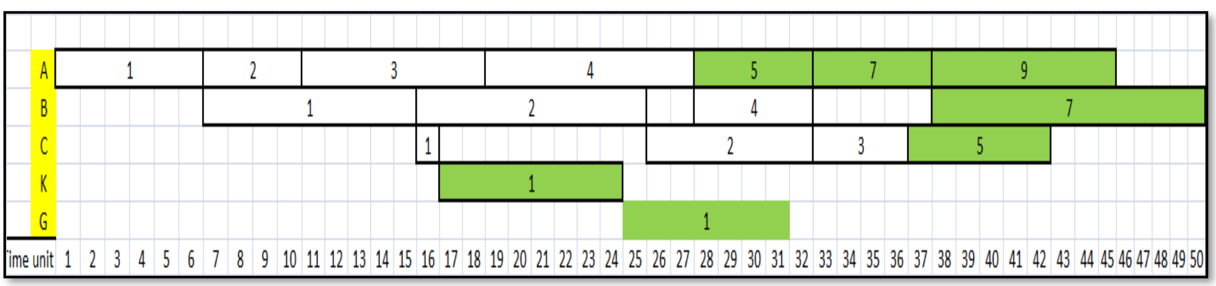

Figure 3.2 Gantt diagram for the initial part sequence in cell 1

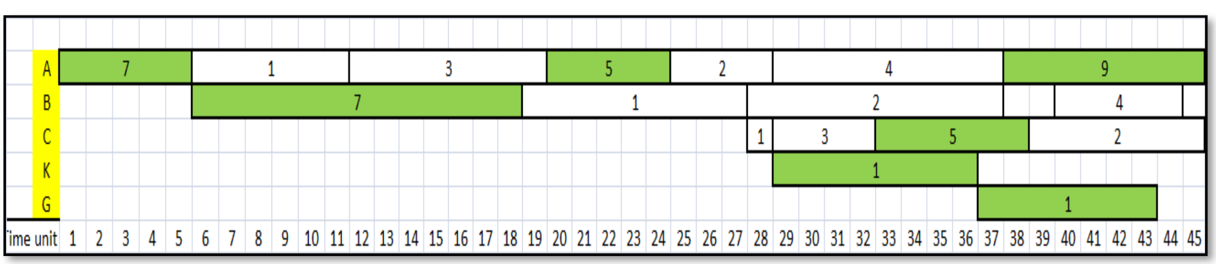

Figure 3.3 The proposed solution using RC-Filter in cell 1

Step 2: Based on the completion time on cell 1 (Table 3.3), update the operation time (of the exceptional elements) of the second cell and optimize the sequence. The operation time used to optimize the family parts of cell two is presented in Table 3.4.

Table 3.4 Operation time for cell 2

		Parts				
Machines		1	5	6	7	8
Cell 2	A	0	24	0	5	0
	B	0	0	0	18	0
	C	0	38	0	0	0
	K	36	7	7	3	5
	L	0	13	8	2	0

Table 3.5 Completion time for cell 2

		Parts				
Machines		8	6	1	5	7
Cell 2	A	0	0	0	24	29
	B	0	0	0	24	47
	C	0	0	0	62	62
	K	5	12	48	69	72
	L	5	20	48	82	84

In this cell, the optimal sequence is **8-6-1-5-7**. The completion time of the exceptional elements will be used to optimize the family parts of the third cell.

Step 3: Based on the completion time on cell 2 (Table 3.5), update the operation time for cell three used to optimize the sequence of parts. Table 3.6 presents optimal solutions for each cell given by RC-Filter proposed in this work. For this example, the obtained makespan is equal to 108.

Table 3.6 Optimal sequence and makespan for each part family

RC-Filter		
Cells	**Optimal sequence**	**Makespan**
1	7-4-9-3-1-2-5	45
2	8-6-1-5-7	84
3	3-5-4-1-2	108

3.7 Application and results

To validate the performance of the RC-Filter methodology proposed in this study (shown in Fig. 3.1), thirteen problems are selected in the literature, and they were resolved using our approach. Table 3.7 describes the size of these thirteen problems (the number of machines m and the number of parts n), the number of cells in each problem, and a comparison between the optimal makespan obtained by our approach and that obtained by other techniques. In these problems, the set-up times were not considered. The operation times were generated randomly from distributions ranging between 0 and 100. Each problem was solved 100 times with different data, and the average makespan was calculated. To solve these thirteen problems, the proposed RC-Filter approach (Fig. 3.1) was implemented using MATLAB on a 2.67 GHz i5 core PC. To solve these problems, the $\Delta\beta$ and the number of iteration were equal to 0.02 and $10^{5,}$ respectively. A summary of the results was shown in Table 3.7.

The average makespan obtained by the RC-Filter was compared with those given by the SVS algorithm and the EGD algorithm. As shown in Table 3.7, eleven problems were improved with a percentage of the error until 17 % compared to that given using the EGD algorithm, and ten problems were improved to that obtained by the SVS algorithm where the percentage of the improvement was until 44 %.

Table 3.7 Obtained Results

No	Problems	Size			RC-Filter	EGD	SVS-algorithm	Improvement	
		m	n	# of cells	Average makespan	Average makespan	Average makespan	Imp % RC-Filter vs. EGD	Imp % RC-Filter vs. SVS
1	Kumar and Vannelli	30	41	2	**618.75**	729.43	727.2	15%	15%
2	Chandrasekharan et al	24	40	7	552.55	555.21	**353.8**	0%	-56%
3	Chandrasekharan et al	24	40	7	539.08	**516.81**	1015.8	-4%	47%
4	Carrie	20	35	4	675.07	**633**	801.8	-7%	16%
5	Harhalakis et al.	20	20	5	**424.99**	514.1	711.5	17%	40%
6	Seifoddini	11	22	3	**571.17**	602.99	1019.2	5%	44%
7	Seifoddini	5	18	2	**660.37**	675.85	897.1	2%	26%
8	Kusiak and Chow	7	8	3	198.45	205.08	**150**	3%	-32%
9	King and Nakormchai	5	7	2	230.94	245.18	**226.4**	6%	-2%
10	Waghodera and Sahu (1984)	5	7	2	**232.23**	273.67	408.3	15%	43%
11	Waghodera and Sahu (1984)	5	7	2	**234.3**	238.98	372.3	2%	37%
12	Waghodera and Sahu (1984)	5	7	2	**312.56**	375.44	425.8	17%	27%
13	Waghodera and Sahu (1984)	5	7	2	**317.15**	369.58	383.7	14%	17%

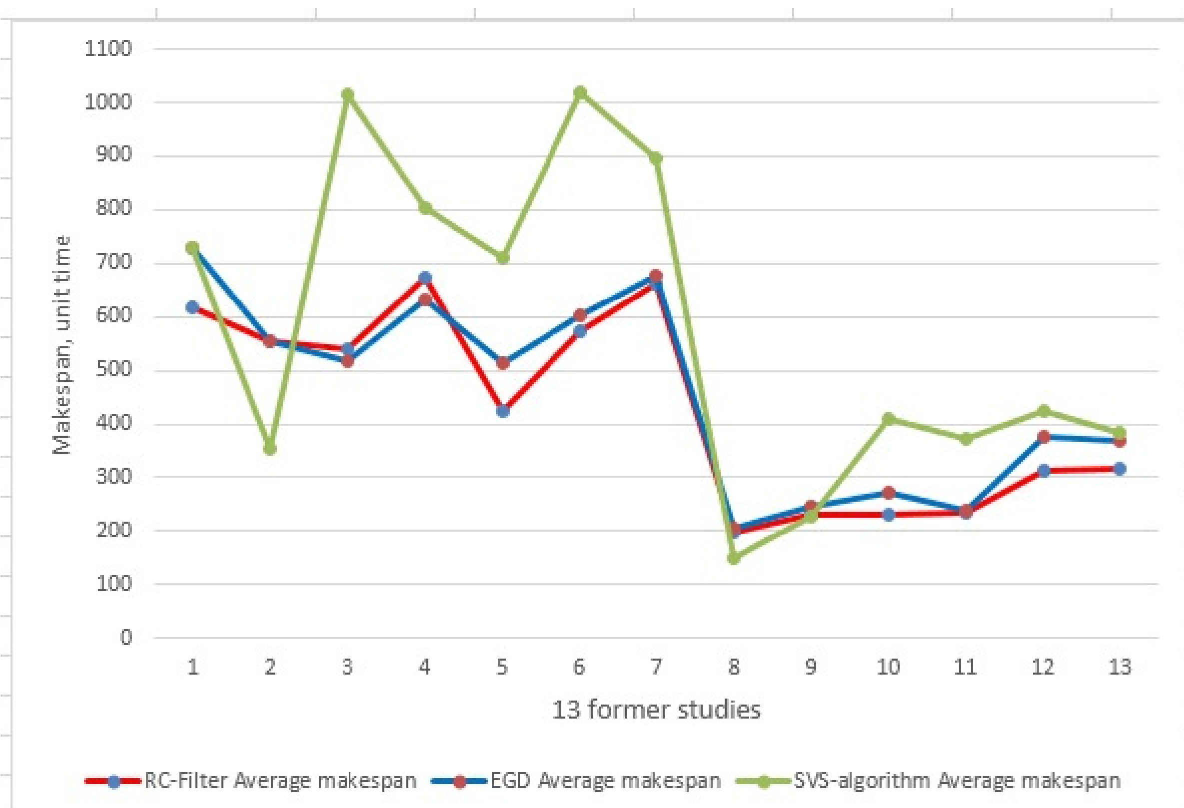

Figure 3.4 The graph chart shows the resolt obtained in table 3.7

3.8 Case study: application and results

For more illustration of the performance of the proposed approach, a case study was used. The RC-Filter was applied to optimize a big size problem. In this case, there are forty (40) parts and twenty (24) machines. This problem was proposed by (Abdallah and Dao, 2011) and was optimized using the EGD approach. These 24 machines proposed in this problem were grouped into seven cells to makes these 40 parts. The incidence matrix of this problem is shown in Table 3.8. The cell system design is represented in Table 3.8. The processing times represents this case is presented in Table 3.8. Seventeen exceptional elements require operations outside where they are affected. Setup times are not considered in this example. To obtain the best solution, the following parameters were used: $\Delta\beta = 0.01$, and the number of iterations were set to 10^5; these parameters were obtained after several tests. The algorithm was implemented using MATLAB on a 2.67 GHz i5 core PC.

Table 3.8 Incidence matrix (2011)

Machines	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
A	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
B	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0
C	0	1	0	0	0	0	0	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
D	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	0
E	0	0	0	0	1	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0
F	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	1	0	0
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
H	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0
I	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	1
J	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
K	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0
L	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0
M	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
N	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
O	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0
P	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	1	0
Q	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	1
R	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0
S	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	1
T	0	1	0	0	0	0	0	0	0	0	1	1	0	0	1	0	0	0	1	0	0	0	1	1	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0
U	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
V	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
W	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
X	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0

Table 3.9 The manufacturing cells with exceptional elements (2011)

Machines		30	18	5	26	27	4	20	7	6	29	40	32	3	25	35	36	22	10	14	13	1	33	9	16	17	31	12	24	15	34	23	11	2	28	21	38	8	39	19	37
cel 11	F	1	1	1	1	1	0																														1				
	H	1	0	1	1	1	1																																		
	R	1	1	1	1	1	1																																		
	L	1	1	1	0	1	1	1																					1												
	O	0	1	1	1	1	1															1																			1
cel 12	J				1			1	1	1	0	0																													
	Q							1	1	1	1	1															1														
	I							0	1	1	1	1											1																		
cel 13	G											1	1	0	1																										
	W												1	1	0																										
	X												1	1	0																			1							
	N												0	1	1					1					1																
cel 14	E			1												1	1	1	1	1	0																				
	S											1				1	1	1	1	1	1																				
	K															1	1	1	1	0	1																				
	B															0	1	1	1	1	1		1																		
cel 15	U																		1			1	1	1	1	0															
	M																					1	1	1	1	1															
	A																					0	1	1	1	1														1	
	V																					1	1	0	1	1															
cel 16	C																										0	1	1	1	1	1	1	1							
	T																										1	1	1	1	1	1	1	1						1	
cel 17	D																							1											1	1	1	1	1	1	0
	P												1																						0	1	1	1	1	1	1

Table 3.10 The processing times of case study (2011)

Machines		30	18	5	26	27	4	20	7	6	29	40	32	3	25	35	36	22	10	14	13	1	33	9	16	17	31	12	24	15	34	23	11	2	28	21	38	8	39	19	37
cel 11	F	3	8	6	5	1	0																														5				
	H	6	0	5	10	3	5																																		
	R	5	2	3	3	8	4																																		
	L	7	9	4	0	5	10	1																					3												
	O	0	5	7	6	2	3															6																			4
cel 12	J				8			6	2	3	0	0																													
	Q							7	1	8	9	5															6														
	I							0	2	1	2	4											2																		
cel 13	G											2	2	0	9																										
	W												4	10	0																										
	X												7	7	0																			7							
	N												0	9	9					2					6																
cel 14	E			4												5	6	4	9	5	0																				
	S											6				3	5	5	10	4	8																				
	K															8	3	9	9	0	4																				
	B															0	4	3	6	9	10		6																		
cel 15	U																		3			7	4	8	3	0															
	M																					3	9	8	4	7															
	A																					0	8	6	4	2														3	
	V																					9	2	0	5	7															
cel 16	C																										0	4	10	3	3	5	8	5							
	T																										3	2	4	3	2	3	2	1						4	
cel 17	D																							4											2	5	2	4	6	4	0
	P												2																						0	5	3	2	3	2	4

The RC-Filter, presented in figure 3.1, was applied to solve a large size problem (24 machines, 40 parts) represented in table 3.8. The makespan which obtained by the proposed approach was improved regards the given by the EGD algorithm proposed by (Abdallah and Dao, 2011). The obtained makespan was equal to 48, with an improvement of 4 % versus that obtained by the EGD algorithm. The Gantt chart of the feasible solution is shown in Figure 3.4. The obtained processing sequence for part family and the error compared to that obtained by the EGD approach in table 3.11, where the makespan on each cell was calculated.

Table 3.11 Summarized Results

	RC-Filter		**EGD (2011)**		Improv
Cells	Sequence of parts	Makespan	Sequence of parts	Makespan	
1	24-1-20-37-4-27-30-5-26-18-38	46	20-1-24-38-37-4-5-27-26-18-30	50	8.0
2	31-26-40-29-33-20-6-7	40	33-31-29-7-6-40-20-26	48	16.7
3	2-14-25-16-32-40-3	41	14-16-2-25-3-32-40	35	-17.1
4	33-13-14-22-10-36-35-5-40	48	33-13-22-14-10-36-35-5-40	48	0.0
5	10-19-17-16-1-9-33	48	19-17-16-1-33-9-10	46	-4.3
6	19-34-12-15-23-31-11-24-2	39	19-23-34-31-15-11-12-24-2	39	0.0
7	9-21-38-28-37-39-19-32-8	30	38-37-21-19-39-8-28-32-9	49	38.8

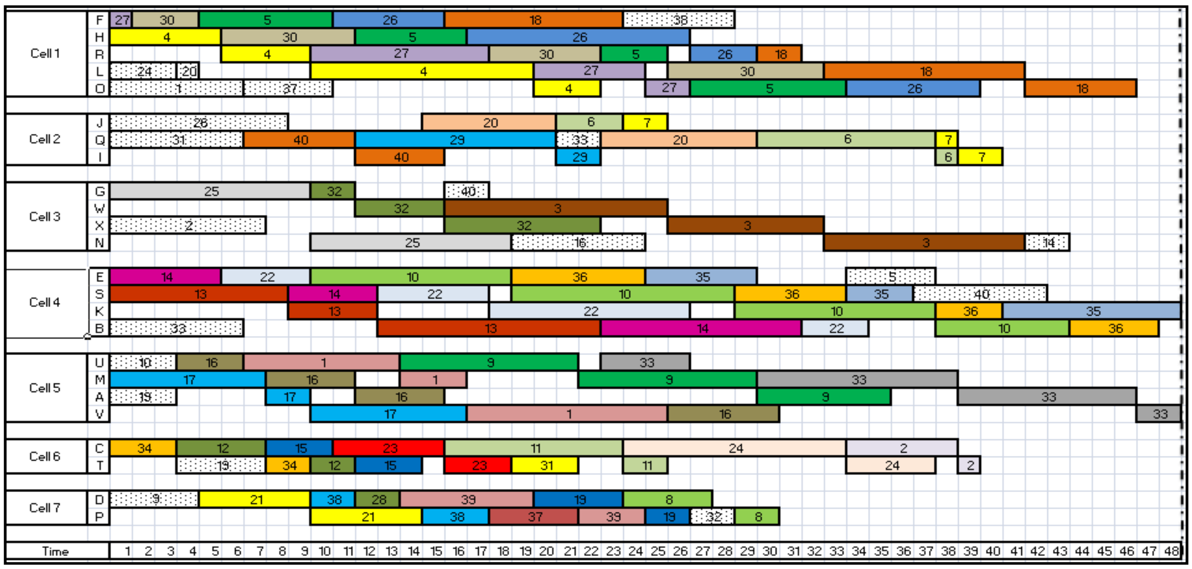

Figure 3.4 Gantt diagram of the optimal solution given by RC-Filter approach

3.9 Conclusion

In this paper, a new algorithm called RC-Filter was used to solve the scheduling optimization problem in the cellular manufacturing system. A case study was presented to prove its efficiency, including exceptional elements. The proposed algorithm (RC-Filter) was applied to solve 13 optimization problems adopted from previous works. The obtained results were compared with that given by the EGD algorithm and SVS-algorithm. 11 problems were improved compared to that given using the EGD algorithm, and ten problems were improved to that obtained by the SVS-algorithm. Also, the proposed approach was applied to a case study (24x40), where the makespan was improved by 4 % compared to the EGD solution.

CHAPTER 4

OPTIMIZATION OF THE CELLULAR MANUFACTURING SCHEDULING USING THE RC-FILTER AND EGD HYBRID META-HEURISTICS

4.1 Abstract

A cellular manufacturing system is a structured system based on the group concept. One of the advantages of this concept is being able to reduce production time. The optimization problem of the cellular manufacturing systems is classified as NP-hard, where the calculation time increases exponentially depending on the size of the problem. The use of meta-heuristic algorithms will be a great solution to solve the NP-hard problem in a reasonable time. In this work, we proposed a new hybrid approach to optimize the sequence of parts in each cell as well as exceptional elements. This hybrid methodology is based on an RC-Filter algorithm and an Extended Great Deluge algorithm. This approach was proposed to optimize the sequence of parts, including exceptional elements in each cell, in order to minimize the makespan. The proposed approach was validated using 13 problems in benchmarks; their results were compared with that given by other algorithms.

4.2 Introduction

The optimization of scheduling in a manufacturing environment is aimed to minimize the makespan or to minimize the total production time. This type of problem is classified as NP-hard, where the calculation time increases exponentially depending on the size of the problem. For this reason, researchers tried to develop techniques, especially meta-heuristics, which give results in reasonable running time. (Sridhar and Rajendran, 1993) proposed a model to minimize the makespan, the flow time, and the idle time in the cell and without introducing the exceptional elements. (Abdallah and Dao, 2011) developed a model to minimize the makespan and the flow time in a cell manufacturing environment, including the exceptional elements, the proposed model was based on an extended great deluge algorithm. A methodology called SVS-algorithm was proposed by (Solimanpur et al., 2004) to optimize the sequence of parts in cellular manufacturing systems. A model based on ant colony optimization proposed by (Guo et al., 2012) was applied to determine the great sequence of parts in complex

Job-shop problems. A methodology was proposed by (Bilyk et al., 2014) to solve parallel machine scheduling problems.

In this study, we are interested in the manufacturing cell problems, including exceptional elements. With the aim to solve this problem, we proposed a hybrid approach based on two metaheuristic algorithms. The first one was the RC-Filter algorithm developed by (Nahas and Nourelfath, 2014), and the second one was the Extended Great Deluge algorithm introduced by (McCollum et al., 2009).

4.3 Methodology

The proposed hybrid methodology was based on two meta-heuristic algorithms. The first one is the RC-Filter and the second one is the extended great deluge algorithm. These two approaches were implemented together with the aim to determine the best sequence of parts in order to minimize the makespan.

4.4 RC-Filter algorithm

The RC-Filter is a meta-heuristic algorithm inspired by the low-pass filter circuit, which is constituted by a resistor (R) and a capacitor (C) connected in series. The RC-Filter was introduced initially by (Nahas and Nourelfath, 2014), and it was applied in the flow-shop scheduling optimization problems.

The RC-Filter algorithm steps, as described by (Nahas and Nourelfath, 2014), are as follows:

- initialization of parameters: β and $\beta 0$;
- initialization of the maximum number of iteration N and the decreasing rate $\Delta\beta$;
- select initial solution S_0 and set $S = S_0$;
- while the number of iteration is $< N$:

1) Randomly select a solution S* from the neighborhood space:

- calculate $G' = f(S) / f(S^*)$;
- calculate $G = 1/\sqrt{1 + (\beta/\beta 0)^2}$;
- If one of the two conditions is satisfied, $G' \geq 1$ or $G(\beta) > G'$.

2) Set $S = S^*$ and $\beta = \beta - \Delta\beta$

- end while.

4.5 Extended great deluge algorithm

The Extended Great Deluge (EGD) used in this work was introduced by (McCollum et al., 2009). The authors used this algorithm to solve the timetabling problem, where its high effectiveness was confirmed. The EGD algorithm was used widely by (Abdallah and Dao, 2011) in the optimization of the manufacturing cell formation and in the optimization of group scheduling. (Mosbah et al., 2016) used this algorithm also to optimize a neural network model for aeronautical applications.

The steps of the EGD algorithm, as described in (McCollum et al., 2009), are as follows:
Define an initial solution S
Calculate the efficiency f(S) and put B=f(S)
Define the decreasing rate of ΔB=?
While the shutdown condition is not satisfied, make:
Define the neighborhood N(S)
Select a solution S* ϵ N(S) randomly
If (f(S*) ≤ f(S)) or (f(S*) ≤ B)
Accept S*
Decrease the upper limit B=B- ΔB
End if
End while.

4.6 Hybrid meta-heuristic approach

In this study, we are interested in the scheduling of manufacturing cells, including the exceptional elements. To solve this complex problem, a hybrid approach based on two meta-heuristic algorithms was implemented, the RC-Filter and the EGD algorithm, to take advantage of the performance of these two algorithms in order to obtain the best sequence of parts hence to provide the minimum makespan. The Flowchart of the proposed RC-Filter & EGD approach is shown in Fig 4.1.
We are interested in the scheduling of manufacturing cells, including exceptional elements. To solve this complex problem, a hybrid approach based on two meta-heuristic algorithms was

implemented, the RC-Filter and the EGD algorithm, to take advantage of the performance of these two algorithms in order to obtain the best sequence of parts hence to provide the minimum makespan.

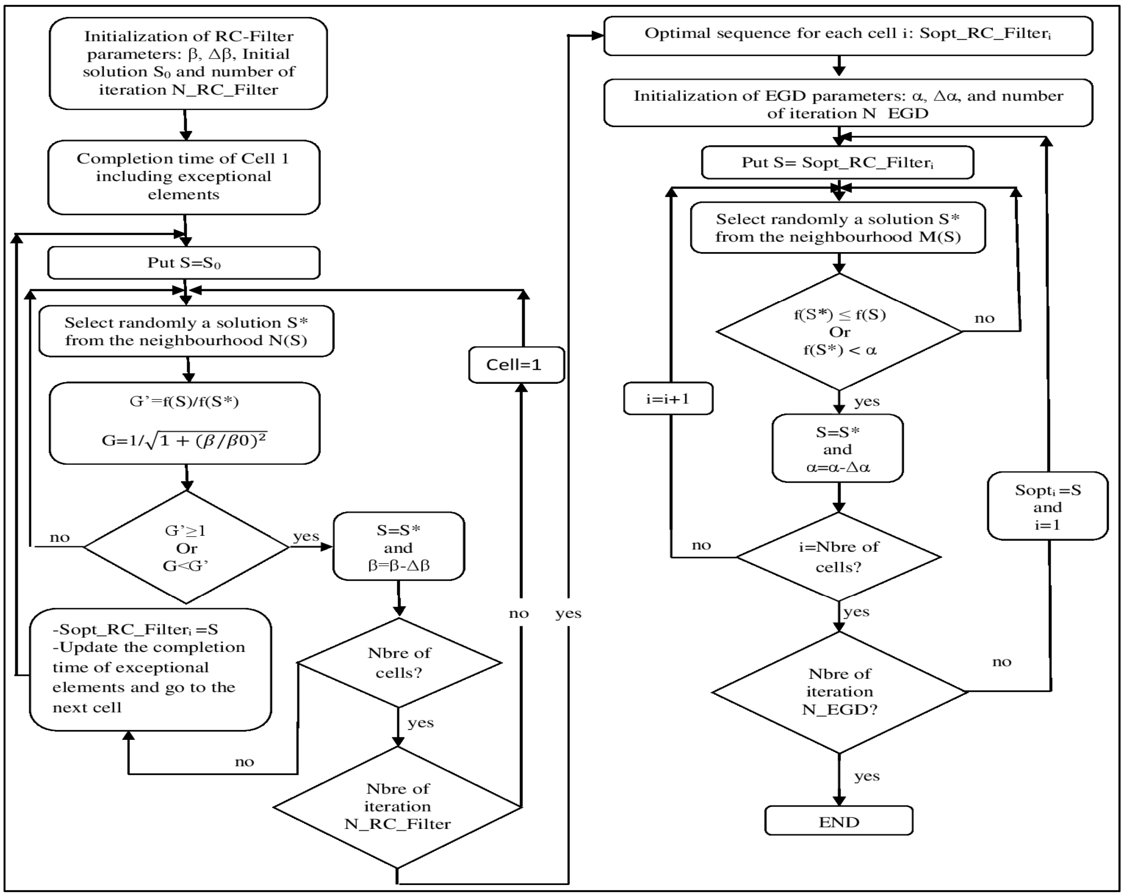

Figure 4.1 Flowchart of the proposed RC-Filter & EGD algorithm

The calculation of the makespan ($f_{(S)}$ in Fig. 4.1) was performed using the model proposed by (Sridhar and Rajendran, 1994); the proposed model are as follows:

n the number of jobs to be scheduled in the cell.

m the number of machines in the cell.

tji the processing time of job j on machine i.

s the set of jobs already scheduled.

q(s, i) the completion time of the partial schedule

s on the machine i.

Fs the flow time of all jobs in s.

The formulation of the problem is:

Initialize T=0, Fs=0 and Ms=0

For j=1 to n do

i = 1 to m do

if tji > 0

then

compute the completion time q(sj,i) of partial

schedule sj

$$q\,(sj,i)=\max[q(s,i);\, T]+ tji \tag{4.1}$$

update

$$T = q(sj,\, i) \tag{4.2}$$

else

$$q(sj,i)= q(s,i) \tag{4.3}$$

The total flowtime of jobs in sj is:

$$Fsj = Fs + T \tag{4.4}$$

The makespan α sj of the partial schedule sj is:

$$Msj = \max\,(Ms\,,\, T) \tag{4.5}$$

In the Fig. 1, the objective function f is

$$fsj = Msj$$

The optimization process of the hybrid approach proposed in this work was done according to the following steps:

Initialization of the RC_Filter parameters: β, Δβ, the initial solution S_0 and the number of iteration N_FC_Filter and give the completion time of the cell one, including exceptional elements.

Put $S=S_0$

Define the neighborhood N(S) and select randomly $S^* \epsilon\ N_{(S)}$

Calculate $G' = f_{(S)} / f_{(S^*)}$

Calculate $G=1/\sqrt{1+(\beta/\beta 0)^2}$

If G′ ≥ 1 and G(β) > G′ are not satisfied, go to step 3

If one of the two conditions satisfied: $G' \geq 1$ or $G(\beta) > G'$

Put S=S* and decrease $\beta=\beta-\Delta\beta$

If the number of cells is not reached:

Put Sopt_RC_Filter=S

Update the completion time of exceptional elements and go to the next cell (Cell =Cell+1).

Go to step 2

If the number of cells is reached:

If the number of iteration < N_RC_Filter

Initiate the number of cells (Cell=1)

Go to step 3

If the number of iteration is reached: Go to the EGD section (refining the optimal solution Sopt_RC_Filter using EGD algorithm).

Initialization of EGD parameters: α, $\Delta\alpha$, the number of iteration N_EGD and the cell number i=1

Initialization of the solution S of the cell i: S=Sopt_RC_Filteri

Define the neighborhood $M_{(S)}$ and select S*ϵ M(S) randomly

If $f_{(S^*)} \leq f_{(S)}$ and ($f_{(S^*)} \leq \alpha$) are not satisfied, go to step 12

If one of the two conditions satisfied: $f_{(S^*)} \leq f_{(S)}$ or ($f_{(S^*)} \leq \alpha$)

Put S=S* and decrease $\alpha=\alpha-\Delta\alpha$

If the number of cells is not reached:

Increase the number of cells: i =i+1

Go to step 12

If the number of cells is reached:

If the number of iteration < N_EGD

Put Sopti=S

Initiate the number of cells (i=1)

Go to step 11

If the number of iteration is reached

Save the solution Sopti

END

4.7 Computational results

In this section, we present an application of the proposed approach to different problems. The performance of the proposed hybrid approach was compared with the RC-Filter, the SVS algorithm, and the EGD algorithm.

4.8 Illustrative example

To illustrate the performance of the proposed methodology, this hybrid meta-heuristic approach was applied to the example proposed by (Solimanpur et al., 2004). The example is composed of ten manufactured parts, using eight machines grouped in three cells. Table I shows the processing times of each part. In this example, there are four exceptional elements that require operations outside their cells where they belong. Part 1 is manufactured in cell two, but it requires one operation on machine E in cell number 1. Part 5 requires two operations outside cell one where it belongs, the first operation is on machine C in cell two, and the second is on machine F in cell 3. The fourth exceptional element is one operation of part 7 on machine C in cell 2. The set-up time for each family part is described in Table 4.2. This example was proposed by (Solimanpur et al., 2004), where the authors proposed a heuristic called the SVS algorithm to solve the scheduling of manufacturing cells. (Abdallah and Dao, 2011) were also used in this example to illustrate the EGD algorithm for the cell scheduling problem. The results given by these two methods were compared with that obtained using the hybrid approach RC-Filter & EGD proposed in this work. The optimal makespan obtained using the SVS algorithm proposed by (Solimanpur et al., 2004) and using the EGD algorithm proposed by (Abdallah and Dao, 2011) were 78 and 56, respectively.

Table 4.1 Operation Time

		Parts									
Machines		5	6	9	10	1	2	4	3	7	8
Cell 1	A	8	5	3	7						
	D	12	15		3						
	E	3	6	9		5					
Cell 2	C	11				4	6	8		8	
	G					10	12	4			
Cell 3	B								2	11	3
	F	4							14	8	6
	H								10	5	

Table 4.2 setup time and sequence of machines for each cell

Cell	A	B	C	D	E	F	G	H	Sequence of process
1	3		2	4	4	1			A-D-E
2			2		3		6		C-G
3		3	3			7		2	B-F-H

To use the hybrid methodology RC-Filter & EGD proposed in this work to define the optimal sequence of parts, including exceptional elements, the operation time was needed to calculate the makespan corresponding to the partial sequence. The idea was to add fictive parts and machines in the cells where the exceptional elements were realized. For example, cell one is made to manufacture parts 5, 6, 9, and 10 but also to realize one operation on part 1 using machine E. This exceptional element was added to the family of the manufactured parts on cell 1. Fictive machines were added in cell 1; these machines were needed to realize exceptional elements of the family part. This step helps to define the completion time of the exceptional elements with the aim to be used in the optimization process of the next family part. For each iteration, the optimization process was as the following steps:

Step 1: The optimization process starts with the first cell; the operation time used to optimize the sequence of parts, including exceptional elements, was presented in Table 4.3. The optimal sequence given by the proposed hybrid method RC-Filter & EGD was **1-5-9-6-10.** The completion time of exceptional elements was calculated to update the operation time of cell 2. According to the obtained optimal sequence, the completion time of part 1 on machine E, including the setup time (Table 4.2), was 8. The completion time of part 5 on machine C and F was 46 and 50, respectively.

Table 4.3 operation time for cell 1

		Parts				
Machines		5	6	9	10	1
Cell 1	A	8	5	3	7	0
	D	12	15	0	3	0
	E	3	6	9	0	5
	C	11	0	0	0	0
	F	4	0	0	0	0

Table 4.4 Operation Time for Cell 2

Parts						
Machines		5	1	2	4	7
Cell 2	E	0	8	0	0	0
	C	46	4	6	8	8
	G	0	10	12	4	0
	F	50	0	0	0	0

Step 2: Based on Step 1, the new operation time used to optimize the family parts of Cell 2 is presented in Table 4.4. In this cell, the optimal sequence is **2-4-7-1-5**. The completion time for

part 1 on machine E is still 8, 46, and 50 for part 5 on machine C and F, respectively, and becomes 27 for part 7 on machine C.

Step 3: Based on cell 2, the operation time used to optimize the sequence of parts is presented in Table 4.5.

Table 4.5 Operation Time for Cell 3

Parts					
machines		5	3	7	8
Cell 3	C	46	0	27	0
	B	0	2	11	3
	F	50	14	8	6
	H	0	10	5	0

The optimal sequence in Cell 3 given by RC-Filter & EGD was **3-7-8-5.** Table 4.6 presents a comparison between optimal solutions given by SVS-algorithm, EGD, and RC-Filter & EGD, as proposed in this work.

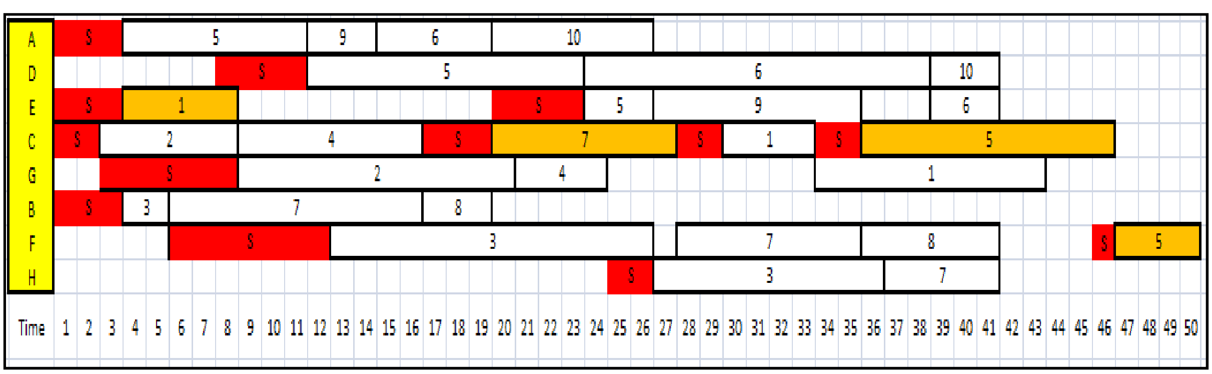

Figure 4.2 Proposed solution using RC-Filter & EGD

Table 4.6 Optimal sequence and makespan for each part family

	SVS - algorithm		EGD		RC-Filter & EGD	
Cells	Optimal sequence	Mak-espan	Optimal sequence	Mak-espan	Optimal sequence	Mak-espan
1	1-6-5-10-9	51	1-6-9-5-10	41	1-5-9-6-10	41
2	5-7-2-4-1	78	7-1-4-2-5	52	2-4-7-1-5	46
3	3-7-8-5	46	3-7-8-5	56	3-7-8-5	50

For this example, the optimal sequence given by our methodology as proposed in this work is shown in the Gantt diagram in Fig. 4.2

4.9 Application and results

To validate the performance of the hybrid RC-Filter & EGD methodology proposed in this study (shown in Fig. 4.1), 13 problems were selected in the literature, and they were resolved using our approach. Table 4.6 described the size of these 13 problems (the number of machines m and the number of parts n), the number of cells in each problem, and a comparison between the optimal makespan obtained by our approach and that obtained by other techniques. In these problems, the set-up times were not considered. The operation time was generated randomly from distributions ranging between 0 and 100. Each problem was solved 100 times with different data, and the average makespan was calculated.

To solve these 13 problems, the RC-Filter & EGD hybrid approach (Fig. 4.1) provides the best results using the following parameters: For the EGD parameters: α= makespan given by RC_Filter, $\Delta\alpha$=0.01, N_EGD=10000. The proposed approach was implemented using MATLAB on a 2.67 GHz i5 core PC. A summary of the results was shown in Table 4.6. The average makespan obtained by the hybrid RC-Filter & EGD was compared with those obtained by the RC-Filter, the SVS-algorithm, and the EGD algorithm individually; the proposed hybrid approach outperformed all three algorithms individually in the overall 13 problems. Hence the ratio error percentage was improved up to 71 %.

Table 4.7 Obtained Results

No	Problems	Size			RC-Filter	EGD	SVS-algorithm	Hyb RC-Filter + EGD	Improvement		
		m	n	# of cells	Average makespan	Average makespan	Average makespan	Average makespan	Imp % Hyb RC-Filter + EGD vs. RC-Filter	Imp% Hyb RC-Filter + EGD vs. EGD	Imp% Hyb RC-Filter + EGD vs. SVS
1	Kumar and Vannelli	30	41	2	618.75	729.43	727.2	**507.89**	18%	30%	30%
2	Chandrasekharan et al	24	40	7	552.55	555.21	353.8	**305.29**	45%	45%	14%
3	Chandrasekharan et al	24	40	7	539.08	516.81	1015.8	**298.4**	45%	42%	71%
4	Carrie	20	35	4	675.07	633	801.8	**457.1**	32%	28%	43%
5	Harhalakis et al.	20	20	5	424.99	514.1	711.5	**304.03**	28%	41%	57%
6	Seifoddini	11	22	3	571.17	602.99	1019.2	**532.39**	7%	12%	48%
7	Seifoddini	5	18	2	660.37	675.85	897.1	**353.07**	47%	48%	61%
8	Kusiak and Chow	7	8	3	198.45	205.08	150	**97.92**	51%	52%	35%
9	King and Nakormchai	5	7	2	230.94	245.18	226.4	**219.5**	5%	10%	3%
10	Waghodera and Sahu (1984)	5	7	2	232.23	273.67	408.3	**200.31**	14%	27%	51%
11	Waghodera and Sahu (1984)	5	7	2	234.3	238.98	372.3	**188.66**	19%	21%	49%
12	Waghodera and Sahu (1984)	5	7	2	312.56	375.44	425.8	**203.45**	35%	46%	52%
13	Waghodera and Sahu (1984)	5	7	2	317.15	369.58	383.7	**194.01**	39%	48%	49%

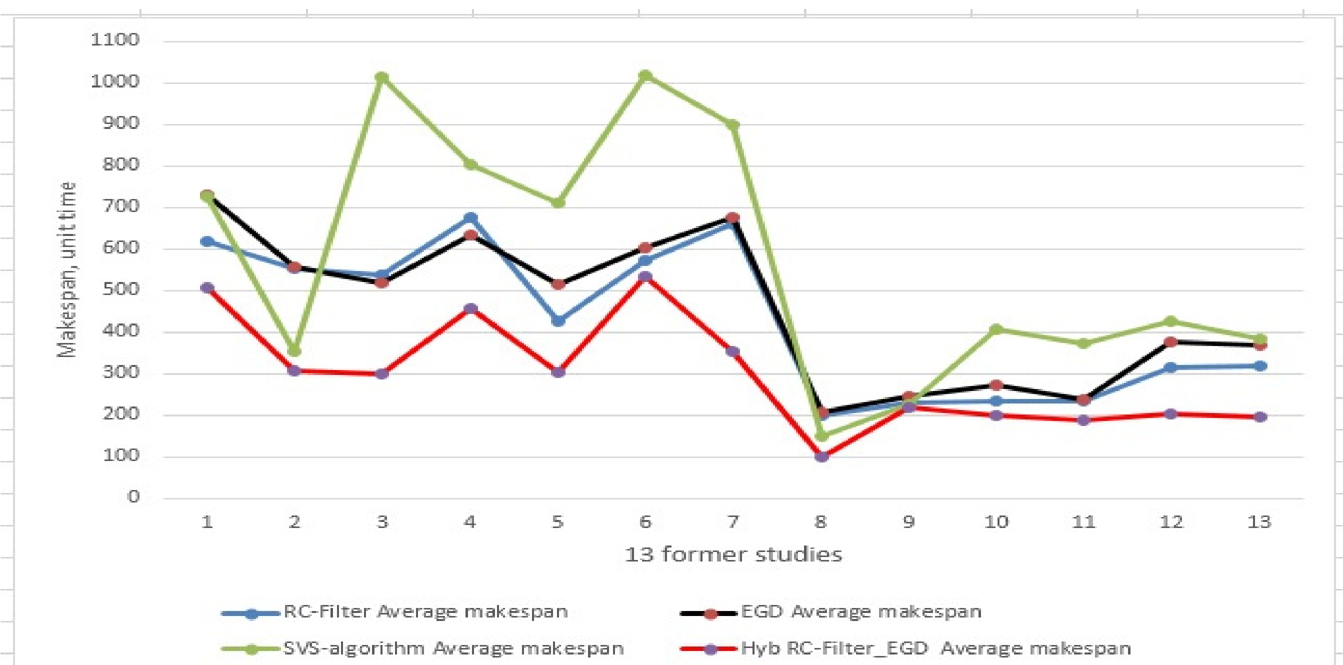

Figure 4.3 the graph chart shows the result obtained in table 4.7

4.10 Conclusion

This work addresses the optimization of group scheduling in cellular manufacturing systems based on meta-heuristic algorithms. An optimization hybrid approach based on the RC-Filter algorithm and extended great deluge algorithm was proposed with the aim to determine the optimal sequence of parts in each cell, including exceptional elements. The benefit of the proposed hybrid approach was very simple to be implemented and adapted to some common scheduling problems. Not only in the 13 problems when it was processed, but also in the illustrative example, the results given by the proposed hybrid approach based on meta-heuristic algorithms, the RC-Filter, and the EGD are powerful techniques, and they produced better results on all treated problems with an exceptional elements.

CHAPTER 5

OPTIMIZATION OF PRODUCTION SCHEDULING BY COMBINING A CELLULAR ENVIRONMENT AND JOB SHOP MANUFACTURING PROCESS USING SIMULATED ANNEALING APPROACH

5.1 Abstract

A manufacturing cell environment is generally the most effective environment at the level of minimization of makespan, the flow time, and the handling. On the other hand, in most cases, a cell production environment requires the execution of exceptional elements. This task generates many delays and intercellular movements. This problem is considered as a high challenge to be resolved with the aim of getting not only the minimum makespan with the exceptional elements but also with the minimum intercellular movements. In this work, a methodology was proposed called simulated annealing meta-heuristic algorithm in order to obtain the best sequence of parts, thus, obtaining the minimum makespan. The work had two stages, and each stage has two parts, as follows:

In part one of the first stage, we used simulated annealing to find the best sequence of exceptional elements without changing the architecture of the cell. It was optimized as a job shop problem because there were a lot of inter-cell movements. In part two, we optimized the sequence in each cell. These two parts represent the first stage of this work. To reduce the inter-cell movements, we used a dynamic cell environment. While in the second stage of this work, a dynamic manufacturing cell was used. This stage comprises of two parts. I the first part, new cells were designed using the exceptional elements only. Likewise, the machines used for the manufacturing of exceptional elements were moved to other cells. During the first part, the exceptional elements were manufactured from a specific cell's architecture. The aim of this part was to give a minimum of inter-cellular movements and handling. The second part of this stage was to back the configuration of the original cells, and the sequences of the parts were optimized in each one. The optimization of the sequence of the parts was done using the simulated annealing algorithm.

5.2 Introduction

The performance of companies depends on their manufacturing process and their optimal resource exploitations. For this reason, it is very important that companies have a good manufacturing system. Many manufacturing systems can be used and adapted, more precisely, the manufacturing cell system. This manufacturing environment has to be optimized to get the maximum benefits of this specific manufacturing organization. The optimization of scheduling is one of the important tasks of the manufacturing cell process. The scheduling problems were classified as NP-hard, where to get the optimal solution, very high calculation time and cost were needed. To resolve this issue, many researchers proposed different techniques, especially the ones based on meta-heuristic algorithms. Meta-heuristic algorithms were a very good alternative to get good results in reasonable running time (Alzidani and Dao, 2019). On the other hand, the "Job shop production system" is known as the manufacturing system used for the production of a wide variety of products and low volume. It is the best process to produce high divergence-designed products within low quantities. This manufacturing is a flexible flow (Supsomboon and Vajasuvimon, 2016). There is a problem with creating a "job-shop scheduling," it is one of the most difficult problems related to manufacturing, also known as the "Job-Shop Scheduling Problem" (JSP) (Asadzadeh, 2016). The result of JSP finds the allocation of resources for one of each time value. As the production scheduling increases, the task completion time decreasing, increase in the capacity utilization & overall efficiency (Shukla et al., 2018). However, there is a probabilistic technique that is used to find out the approximation of the global optimum, and it is generally the meta-heuristic approach for the "approximate global optimization." It is the most preferred method of heuristics for the solution of optimization problems. The process of annealing tells about the "optimal molecular arrangements" of particles of metals (Eren et al., 2017).

In this paper, we focused on scheduling optimization in manufacturing cell problems, including exceptional elements. The objective was to propose the best sequence of parts in each cell, including exceptional elements that give the minimum of Makespan with the use of machines available in the company without any external solutions, especially for EE as subcontracting. In this study, we proposed a tool based on simulated annealing to solve this problem.

5.3 Literature review

Many researchers and publications focused on the analysis of manufacturing cell problems. The majority of these studies discuss and analyze static manufacturing cells. There are three planning tasks that are necessary for the manufacturing cell environment (Wu et al., 2007), (Akturk, 2011). These three tasks can be solved independently. The first task is to group the machines that will make a family of similar parts; the obtained groups represent the manufacturing cells. The second task is to solve a layout problem. The cells should be positioned in the workshop, and the machines should also be positioned in each cell. The third task is the scheduling problem; the sequence of the parts has to be optimized in each cell. This task becomes more complicated when we have exceptional elements where some parts have to be manufactured in more than one cell. The first and second tasks have been given more attention by researchers (Kia et al., 2012; Ming Wut and Chou, 2009; Papaioannou and Wilson, 2010). On the other hand, some researchers focus on scheduling problems to proposed tools in other to get full benefits of the manufacturing cell systems, especially with an exceptional element, which is the aim of our work (Janis and Bade, 2016).

Many researchers proposed several approaches in order to solve group scheduling problems. The majority of these studies analyzed heuristic and meta-heuristic techniques where acceptable results were given to reasonable computation time. Meta-heuristic approaches remain the strong tools for solving this type of problem, ranked NP-hard while minimizing the running time. From a large variety of meta-heuristic tools, we can cite a study proposed by (Liou and Liu, 2010); the authors proposed a tool based on the particle swarm optimization approach to minimize the completion time by determining the best sequence of jobs in each cell and the sequence of cells. Thereafter, this work was improved by (Liou et al., 2013) by using a hybrid tool based on particle swarm and genetic algorithm with the aim of minimizing and integrating the sum of completion time with removal and job transportation time (Janis and Bade, 2016).

A methodology was proposed by (Sridhar and Rajendran, 1994) based on a genetic algorithm with the aim to optimize the family and job scheduling in flowline-based manufacturing cells (Sridhar and Rajendran, 1994). To propose a solution for group scheduling and machining speed selection problems (Zolfaghari and Liang, 1999) developed a hybrid tabu search and simulated annealing methodology (Janis and Bade, 2016). (Abdallah and Dao, 2011) used a meta-heuristic methodology called Extended Great Deluge (EGD) to develop an optimization tool to the scheduling manufacturing problem with the aim of minimizing the Makespan and the flowtime in the manufacturing cell process. The authors also proposed a solution for exceptional elements. (Sridhar and Rajendran, 1993) proposed a model to optimize the manufacturing cells and also to minimize the Makespan, the flow time, and the idle time. Their solution excluded exceptional elements. (Solimanpur et al., 2004) proposed a heuristic called SVS-algorithm to minimize the Makespan in getting the optimal sequence of parts in à cellular manufacturing process.

The meta-heuristic algorithm, the ant colony, was used by (Guo et al., 2012) to determine the optimal sequences of a part in a complex job-shop manufacturing environment. (Neufeld et al., 2019) studied the scheduling flowline manufacturing cells by using constructive heuristics and a "simulated annealing algorithm" to generate schedules. Their results showed that the heuristic approach is better to understand and highlight the necessity. (Kumar and Vannelli, 1986) introduced a "similarity score-based two-phase heuristic approach" to resolve the layout of a "dynamic cellular facility" for manufacturing systems. The "dynamic cellular facility layout problem" (DCFLP) is a quite famous NP-hard problem. If DCFLP is resolved effectively, then the manufacturing cost of 10% to 30% can be reduced. So, Kumar et al. decided to apply the said approach to resolve DCFLP optimally by manufacturing multiple products multiple times. Their results have shown that the proposed approach has the ability to solve the DCFLP optimally within a reasonable time.

5.4 Problem description

As it is already discussed, manufacturing is such an important process all over the world. In order to fulfill the public requirements, the manufacturing system should be in the best working condition. But, like any other field/industry, manufacturing has its own problem, which causes huddles to fulfill the product requirements. In our study of interest, the problem of the manufacturing system is the parts scheduling or "Job-shop Scheduling." This doesn't allow the system to produce the products in higher quantities. In order to overcome this problem, we decided to combine the cellular environment and job-shop scheduling SA algorithm approach.

5.5 Simulated annealing

Metaheuristic techniques are potential tools to solve complex optimization problems. Metaheuristic algorithms can give a very good and very fast solution. These methodologies can be easily adapted and used in a large variety of combinatory problems. One of these techniques is the simulated annealing (SA) algorithm. The objective of the SA is to drive the material to its equilibrium state using minimum energy. For this reason, the material was heated to a high temperature; after that, it cooled gradually. Inspired by this thermodynamic phenomenon (Kirkpatrick et al., 1983) proposed an optimization approach. The mechanism of the SA algorithm is presented in the following steps:

Heat the material to a high initial temperature T=T0

- It is important to keep T constant, the material evolved to the thermodynamic equilibrium state using a small modification of the structure. Each modification generates a small energy ΔE. These modifications are generated where the probability of the energy ΔE > 0, based on the theory of Boltzmann and the metropolis algorithm, this probability is calculated as follows: $P = e^{\frac{-\Delta E}{K.T}}$, where K is the constant of Boltzmann
- Where the equilibrium state is reached, the temperature T is reduced slightly;
- The process continues until the final state of the material will be reached.

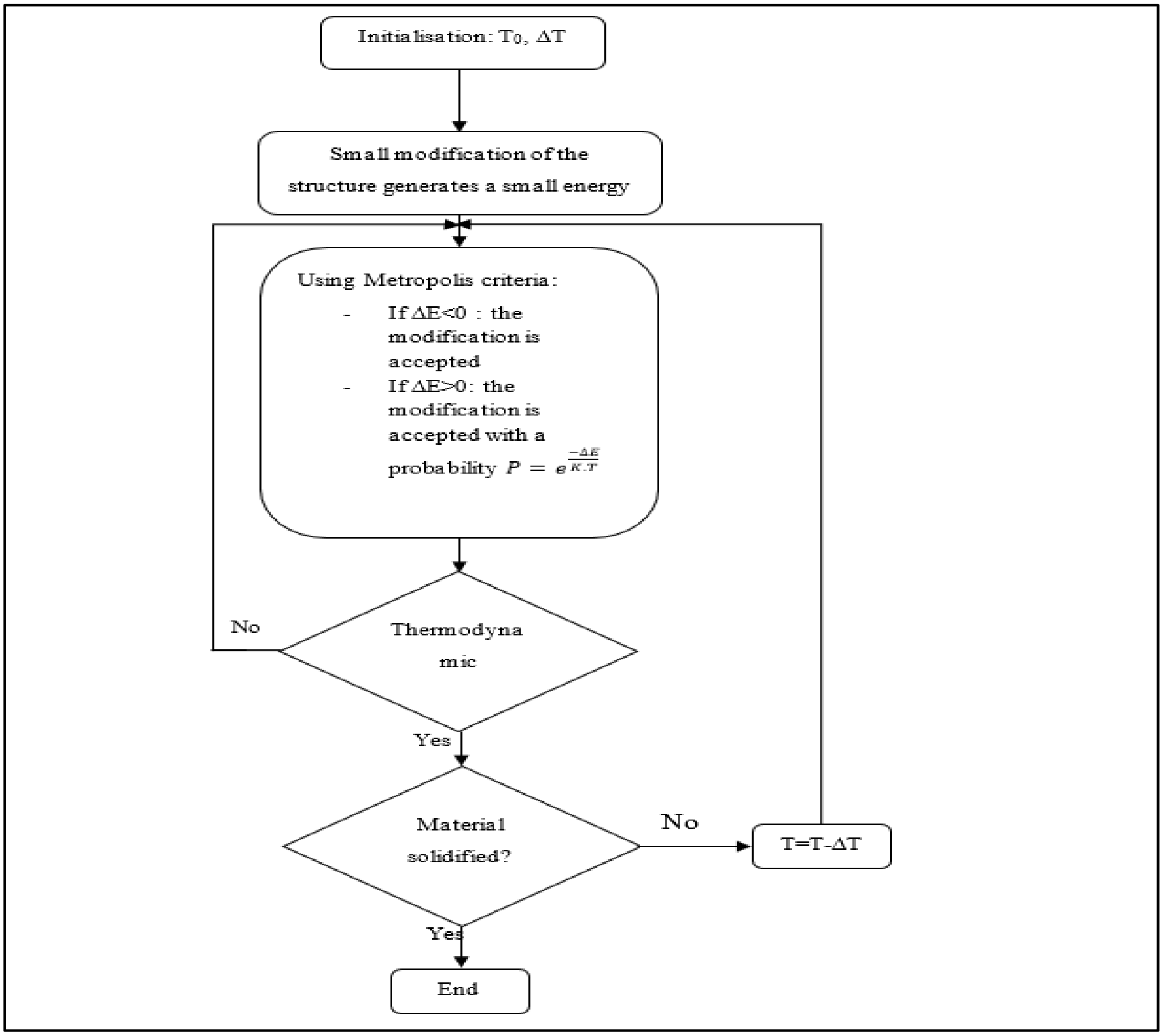

Figure 5.1 Simulated annealing diagram

Figure 6.1 describes the general diagram of the SA. The SA methodology is very easy and fast to be adapted to optimization problems. The SA, like other metaheuristic algorithms, needs some adjustments at the choice of initial parameters. The SA needs a good initial temperature T and the elementary modification ΔT. These two parameters are chosen manually by trial and test.

5.6 Sequence optimization techniques

The aim of this work is to determine the optimal sequence of parts to get the minimum execution time in each manufacturing cell. This task becomes more complicated with exceptional elements; the optimization of the sequence should take into account the responsibility of machines in other cells. The iterative optimization process was used to determine the optimal solution; this method starts from a realizable initial solution. During the optimization process, a new neighbourhood solution was tested in each iteration to get the best solution. In each iteration, the neighbourhood solution was obtained from a small modification of the actual solution. In our work, the neighbour solution was obtained by the permutation of two parts in the sequence chosen randomly.

5.7 Makespan calculation

To get the optimal solution, we need to know the makespan corresponding to each solution during the optimization process. For this aim, we refer to the heuristic of (Sridhar and Rajendran, 1993) to calculate the makespan. Their proposed heuristic is described as follows:

n the number of jobs to be scheduled in the cell.

m the number of machines in the cell.

t_{ji} the processing time of job j on machine i.

s the set of jobs already scheduled.

$q(s, i)$ the completion time of the partial schedule

s on the machine i.

Fs the flow time of all jobs in s.

The formulation of the problem is:

Initialize $T=0$, $Fs=0$ and $Ms=0$

For $j=1$ to n do

$i = 1$ to m do

if $t_{ji} > 0$

Then

compute the completion time $q(s_j,i)$ of partial

schedule s_j

$$q(s_j,i)=\max[q(s,i); T]+t_{ji} \tag{5.1}$$

update

$$T = q(s_j, i) \tag{5.2}$$

Else

$$q(s_j,i)= q(s,i) \tag{5.3}$$

the total flowtime of jobs in s_j is:

$$F_{sj} = F_s + T \tag{5.4}$$

The makespan α_{sj} of the partial schedule s_j is:

$$M_{sj}= \max (M_s , T) \tag{5.5}$$

The objective function f is:

$$f_{sj} = M_{sj}$$

5.8 Proposed methodology

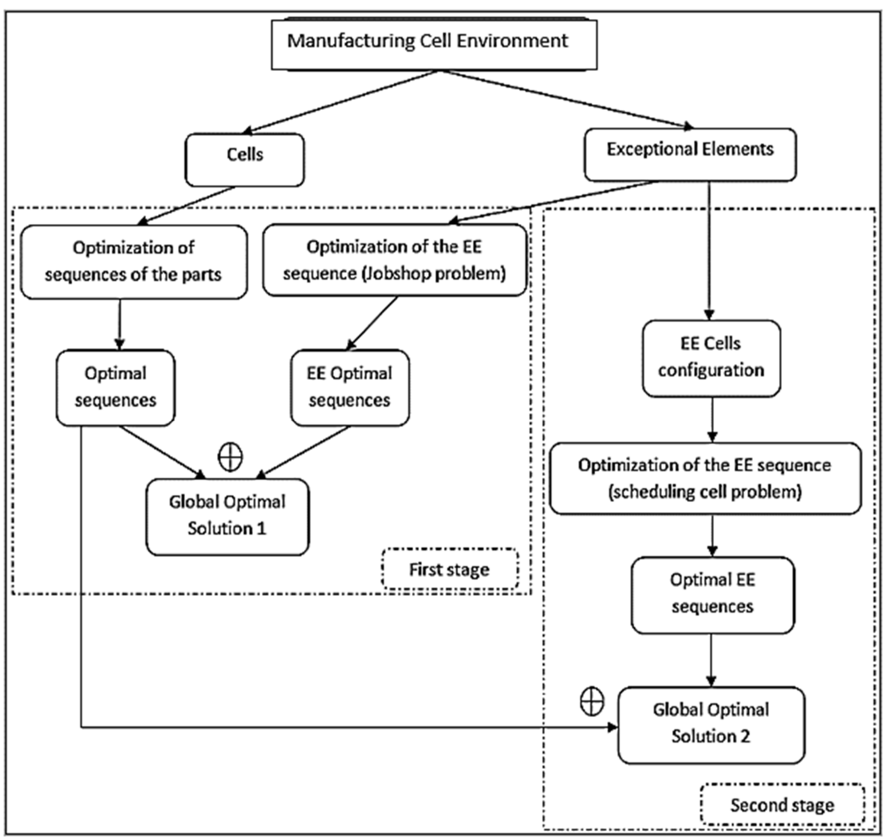

Figure 5.2 The proposed methodology

5.9 Case study application

To illustrate the performance of the proposed approach, the model was tested using a big size problem. The treated example was composed of 40 parts and 24 machines. This problem was initially proposed by (Abdallah and Dao, 2011). The initial incidence matrix is represented in Table 5.1. Using this table, the manufacturing cell was designed by (Abdallah and Dao, 2011) using EGD methodology (Table 5.2). This manufacturing environment compounds seven cells and 20 exceptional elements, which is the biggest challenge to schedule them (Table 5.3).

Table 5.1 Matrix of incidence (2011)

Machines	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
A	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
B	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0
C	0	1	0	0	0	0	0	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
D	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	0
E	0	0	0	0	1	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0
F	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	1	0	0
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
H	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0
I	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	1
J	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
K	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0
L	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0
M	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
N	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
O	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0
P	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	1	0
Q	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	1
R	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0
S	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	1
T	0	1	0	0	0	0	0	0	0	0	1	1	0	0	1	0	0	0	1	0	0	0	1	1	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0
U	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
V	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
W	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
X	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0

Table 5.2 Manufacturing cell architecture (2011)

		Parts																																					
	Machines	30	18	5	26	27	4	20	7	6	29	40	32	3	25	35	36	22	10	14	13	1	33	9	16	17	31	12	24	15	34	23	11	2	28	21	38	8	39	19	37
cel 11	F	1	1	1	1	1	0																														1				
	H	1	0	1	1	1	1																																		
	R	1	1	1	1	1	1																																		
	L	1	1	1	0	1	1	1																					1												
	O	0	1	1	1	1	1															1																			1
cel 12	J				1			1	1	1	0	0																													
	Q							1	1	1	1	1															1														
	I							0	1	1	1	1											1																		
cel 13	G											1	1	0	1																										
	W												1	1	0																										
	X												1	1	0																			1							
	N												0	1	1					1					1																
cel 14	E			1												1	1	1	1	1	0																				
	S											1				1	1	1	1	1	1																				
	K															1	1	1	1	0	1																				
	B															0	1	1	1	1	1		1																		
cel 15	U																		1			1	1	1	1	0															
	M																					1	1	1	1	1															
	A																					0	1	1	1	1														1	
	V																					1	1	0	1	1															
cel 16	C																										0	1	1	1	1	1	1	1							
	T																										1	1	1	1	1	1	1	1						1	
cel 17	D																							1											1	1	1	1	1	1	0
	P												1																						0	1	1	1	1	1	1

Table 5.3 Processing times of the case study (2011)

		Parts																																					
	Machines	30	18	5	26	27	4	20	7	6	29	40	32	3	25	35	36	22	10	14	13	1	33	9	16	17	31	12	24	15	34	23	11	2	28	21	38	8	39	19	37
cel 11	F	3	8	6	5	1	0																														5				
	H	6	0	5	10	3	5																																		
	R	5	2	3	3	8	4																																		
	L	7	9	4	0	5	10	1																					3												
	O	0	5	7	6	2	3															6																			4
cel 12	J				8			6	2	3	0	0																													
	Q							7	1	8	9	5															6														
	I							0	2	1	2	4											2																		
cel 13	G											2	2	0	9																										
	W												4	10	0																										
	X												7	7	0																			7							
	N												0	9	9					2					6																
cel 14	E			4												5	6	4	9	5	0																				
	S											6				3	5	5	10	4	8																				
	K															8	3	9	9	0	4																				
	B															0	4	3	6	9	10		6																		
cel 15	U																		3			7	4	8	3	0															
	M																					3	9	8	4	7															
	A																					0	8	6	4	2														3	
	V																					9	2	0	5	7															
cel 16	C																										0	4	10	3	3	5	8	5							
	T																										3	2	4	3	2	3	2	1						4	
cel 17	D																							4											2	5	2	4	6	4	0
	P												2																						0	5	3	2	3	2	4

5.10 Application of the proposed methodology

A. First stage

In this work, we proposed a tool that is compounded by two stages. The first stage, as shown in Figure 6.2-First stage. The first stage is represented by the following parts:

- Firstly, EE is manufactured. The optimal sequence of EEs was determined using the SA algorithm. This sub-problem is the equivalent of the optimization of a job shop environment because the machines used to make the EEs are scattered in different manufacturing cells;
- Secondly, the rest parts (without EE) are manufactured, and the sequence of parts in each cell was optimized with the SA algorithm;
- Finally, the global solution was obtained by parts a) and b). The optimal sequence in part b) started as soon as the relevant machinery was available.

5.10.1 Application of the first stage

In the first part, as explained in the previous paragraph, the EEs are extracted from the original matrix of the processing time (Table 5.3). The new matrix, represented by Table 5.4, was treated as a job shop problem. In this case, the used machines belong to different cells. The optimization of the sequence of the parts was done using the SA algorithm, and the makespan was calculated using Sridhar and Rajendran (1993) heuristic presented in paragraph IV. The solution was presented in Figure 5.3; the obtained Makespan to produce EEs is 10 unit time. The optimal process using SA was done with the initial temperature T_0=10, the elementary modification ΔT =0.002, and the number of iteration is equal to 10^5.

Table 5.4 Processing time of EEs

		Parts																
		5	26	20	40	32	10	14	1	33	9	16	31	21	2	38	19	37
Machines	F	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0
	L	0	0	1	0	0	0	0	0	0	0	0	0	3	0	0	0	0
	O	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	4
	J	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Q	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0
	I	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0
	G	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0
	X	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0
	N	0	0	0	0	0	0	2	0	0	0	6	0	0	0	0	0	0
	E	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	S	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0
	B	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0
	U	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0
	A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0
	T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0
	D	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0
	P	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0

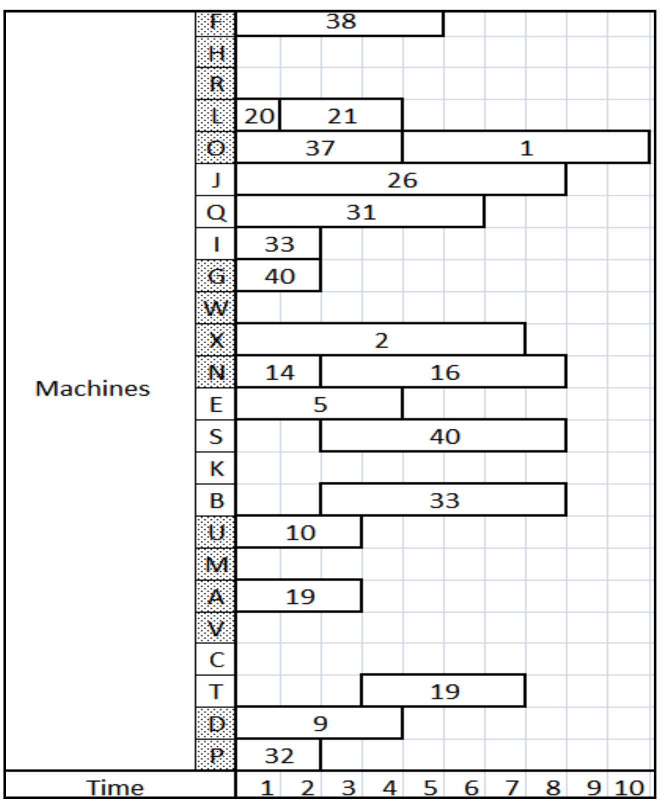

Figure 5.3 Gantt diagram of EEs

The second part was to optimize the part sequences for each cell. The input in this part is represented in Table 5.5. Using the SA algorithm, the part sequences were optimized individually without introducing EEs. The optimal sequences are recapitulated in Table 5.6, where the results were compared with that obtained using the RC-Filter algorithm (2018). The best solutions were obtained by using the following parameters, the initial temperature T0=1000, the elementary modification ΔT=0.006, and the number of iteration = 10^5. As shown in Table 5.6, the obtained solutions using SA are better than those obtained using RC-Filter. The results were improved in 5 cells, and the optimal sequences decreased the makespan for each cell. The global solution described above in part c) is shown in Figure 5.4 and Table 5.7. The global solution combines the optimal solution of EEs and that obtained for each solution where machines start as soon as they finish their tasks for EEs. The proposed tool (Figure. 5.2) was implemented using MATLAB on a 2.67 GHz i5 core PC.

Table 5.5 Processing time matrix without EE

		Parts																																							
Machines		30	18	5	26	27	4	20	7	6	29	40	32	3	25	35	36	22	10	14	13	1	33	9	16	17	31	12	24	15	34	23	11	2	28	21	38	8	39	19	37
Cell 1	F	3	8	6	5	1	0																																		
	H	6	0	5	1	3	5																																		
	R	5	2	3	3	8	4																																		
	L	7	9	4	0	5	10																																		
	O	0	5	7	6	2	3																																		
Cell 2	J							6	2	3	0	0																													
	Q							7	1	8	9	5																													
	I							0	2	1	2	4																													
Cell 3	G												2	0	9																										
	W												4	10	0																										
	X												7	7	0																										
	N												0	9	9																										
Cell 4	E															5	6	4	9	5	0																				
	S															3	5	5	10	4	8																				
	K															8	3	9	9	0	4																				
	B															0	4	3	6	9	1																				
Cell 5	U																					7	4	8	3	0															
	M																					3	9	8	4	7															
	A																					0	8	6	4	2															
	V																					9	2	0	5	7															
Cell 6	C																										0	4	10	3	3	5	8	5							
	T																										3	2	4	3	2	3	2	1							
Cell 7	D																																		2	5	2	4	6	4	0
	P																																		0	5	3	2	3	2	4

Table 5.6 Obtained sequences of parts without EE

	RC-Filter [5]		SA		Improv%
Cells	Optimal Sequence	Makespan	Optimal Sequence	Makespan	
1	4 - 27 - 30 - 5 - 26 - 18	46	4 - 5 - 27 - 26 - 18 - 30	45	2
2	40 - 29 - 20 - 6 - 7	32	40 - 29 - 7 - 6 - 20	30	6
3	25 - 32 - 3	41	25 - 3 - 32	35	15
4	13 - 14 - 22 - 10 - 36 - 35	48	13 - 14 - 22 - 10 - 36 - 35	48	0
5	17 - 16 - 1 - 9 - 33	44	17 - 1 - 16 - 33 - 9	37	16
6	34 - 12 - 15 - 23 - 31 - 11 -24 - 2	39	31 -23 - 34 - 11 - 12 - 24 - 15 - 2	39	0
7	21 - 38 - 28 - 37 - 39 - 19 - 8	25	19 - 37 - 38 - 21 - 39 - 8 - 28	23	8

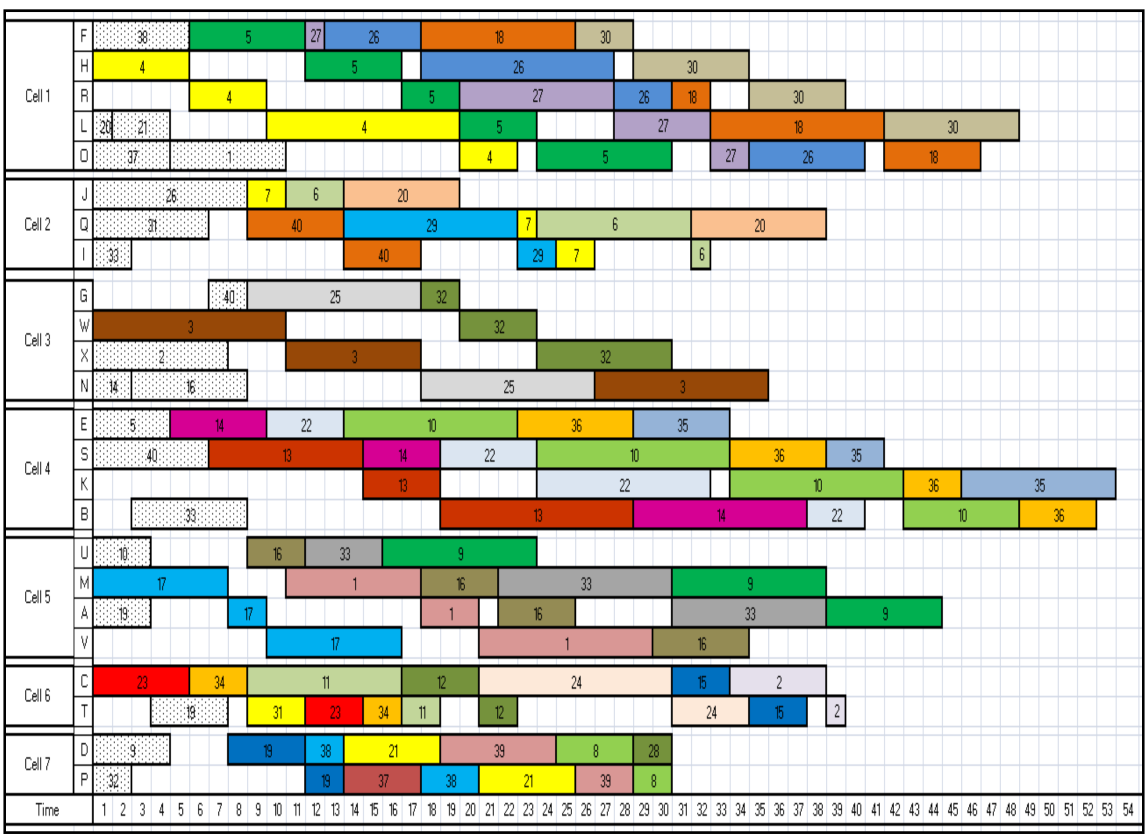

Figure 5.4 Gantt diagram for the global solution obtained using SA

Table 5.7 Global solution including EE

	RC-Filter		SA		Error %
Cells	Optimal Sequence	makespan	Optimal Sequence	makespan	
1	24 - 1 -20 - 37 - 4 - 27 - 30 - 5 - 26 - 18 38	46	20 - 37 - 38 - 21 - 1 - 4 - 5 - 27 - 26 - 18 - 30	48	-4.3
2	31 - 26 - 40 - 29 - 33 - 20 - 6 - 7	40	33 - 31 - 26 - 40 - 29 - 7 - 6 - 20	38	5
3	2 - 14- 25 - 16 - 32 - 40- 3	41	14 - 2 - 40 - 16- 25 - 3 - 32	35	14.6
4	33 - 13 - 14 - 22 - 10 - 36 - 35 - 5 - 40	48	33 - 5 - 40 - 13 - 14 - 22 - 10 - 36 - 35	53	-10.4
5	10 - 19 - 17 - 16 - 1 - 9 - 33	48	10 - 19 - 17 - 1 - 16 - 33 - 9	44	8.3
6	19 - 34 - 12 - 15 - 23 - 31 - 11 -24 - 2	39	19 - 31 -23 - 34 - 11 - 12 - 24 - 15 - 2	39	0
7	9 - 21 - 38 - 28 - 37 - 39 - 19 - 32 - 8	30	9 - 32 - 19 - 37 - 38 - 21 - 39 - 8 - 28	30	0

The first solution proposed in this work was described in Figure 5.2. The first stage to get a good solution for our case. The issue in this solution was the high number of inter-cell movements, therefore a big waste of handling and waiting time, which generates a high cost. Figure 5.4 shows the inter-cell movement of parts 19, 33, and 40 given by our tool, as shown in Figure 5.2 First stage.

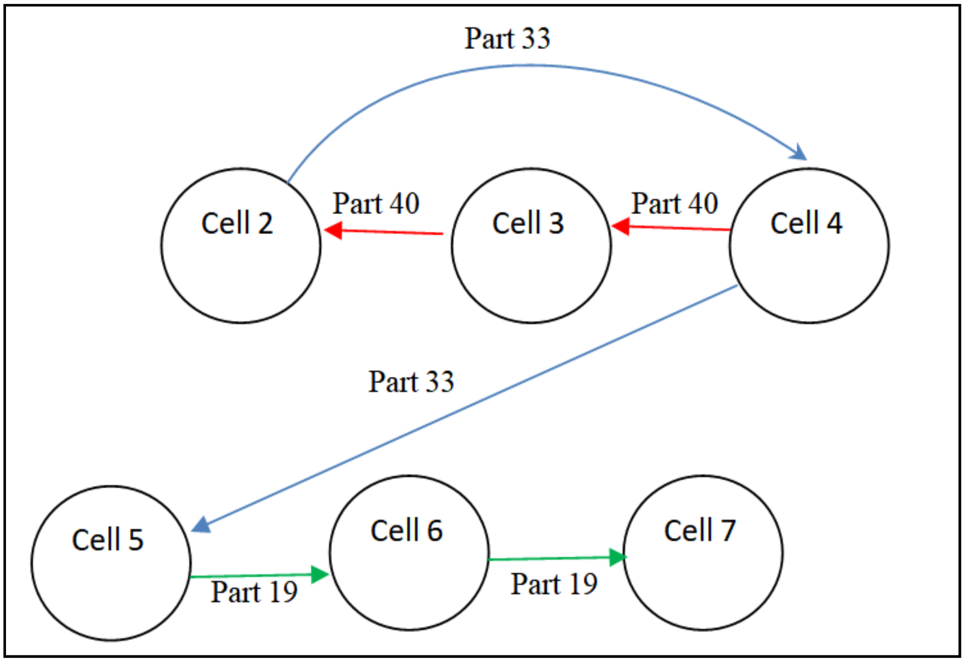

Figure 5.5 Inter-cell movement of parts 19, 33 and 40

5.10.2 Application of the second stage

In other to resolve the problem of the inter-cell movement, mostly when we have a large number of EEs, we proposed the second solution that was shown in Figure 5.2 Second stage. Instead of sending parts from one cell to another, we proposed to reorganize the manufacturing environment. The first part is to move machines needed for the manufacturing of EEs to the specific cells where the parts (need EE jobs) belong. The second part is to come back to the original manufacturing cell architecture, as described in Table 5.3. Using this solution, we can eliminate the inter-cell movement. We need jute to have dynamic manufacturing cells to minimize the handling and waiting time, stock, work power, etc. Table 6.8 describes cell architecture during the first and second parts.

Machine L was in cell 2 to manufacture part 1; after that, it moved to cell 6 to do part 24. Machine O was affected firstly to cell 7 for the EE task of part 37; after that, it moved to cell 5 to manufacture the EE of part 1. The same operation for machine N belongs to cell 4 for EE of part 14; when it finished, it moved to cell 5 to do the EE of part 16.

Table 5.8 Architecture of the cells for the 1st & 2nd parts

First Part_EE manufacture		Second Part_Original manufacturing cell	
Cell	Machines	Cell	Machines
1	H,R,J,E	1	F,H,R,L,O
2	L,Q,G,S	2	J, Q, I
3	W,P	3	G,W,X,N
4	N,K,U	4	E,S,K,B
5	I,B,M,V,O,N	5	U,M,A,V
6	X,C,L	6	C, T
7	F,O,A,T,D	7	D, P

O, N, L: These machines moved to more than one cell.

5.11 Application and results

To validate the performance of the proposed tool based on SA optimization (Figure 5.2), the 13 problems were tested using the proposed approach; these problems were selected in the literature, the set-up times were not considered in these problems. Table 5.9 described the size of these 13 problems (the number of machines m and the number of parts n) and the number of cells in each problem. We compared the obtained results with other tools. These problems were running 100 times with different operation times between 0 and 100. The average makespan was calculated and presented in Table 5.9. The proposed tool was implemented using MATLAB on a 2.67 GHz i5 core PC. The best solutions were obtained using the initial temperature T0=1000, the elementary modification $\Delta T=0.04$, and the number of iteration = 2.10^5.

Table 5.9 Obtained results and comparison with existing approaches

No	Problems	Size			RC-Filter	EGD	SVS-Algorithm	SA	Improvement %		
		m	n	# of cells	Average makespan	Average makespan	Average makespan	Average makespan	SA vs. RC-Filter	SA vs. EGD	SA vs. SVS-Algorithm
1	Kumar and Vannelli	30	41	2	**618.75**	729.43	727.2	716.3	-16%	2%	1%
2	Chandrasekharan et al	24	40	7	552.55	555.21	**353.8**	552.08	0%	1%	-56%
3	Chandrasekharan et al	24	40	7	539.08	516.81	1015.8	**509.49**	5%	1%	50%
4	Carrie	20	35	4	675.07	633	801.8	**626.58**	7%	1%	22%
5	Harhalakis et al.	20	20	5	**424.99**	514.1	711.5	449.82	-6%	13%	37%
6	Seifoddini	11	22	3	**571.17**	602.99	1019.2	619.12	-8%	-3%	39%
7	Seifoddini	5	18	2	660.37	675.85	897.1	**657.64**	0%	3%	27%
8	Kusiak and Chow	7	8	3	198.45	205.08	**150**	187.61	5%	9%	-25%
9	King and Nakormchai	5	7	2	230.94	245.18	**226.4**	228.55	1%	7%	-1%
10	Waghodera and Sahu (1984)	5	7	2	**232.23**	273.67	408.3	245.85	-6%	10%	40%
11	Waghodera and Sahu (1984)	5	7	2	234.3	238.98	372.3	**232.4**	1%	3%	38%
12	Waghodera and Sahu (1984)	5	7	2	312.56	375.44	425.8	**305.09**	2%	19%	28%
13	Waghodera and Sahu (1984)	5	7	2	317.15	369.58	383.7	**311.97**	2%	16%	19%

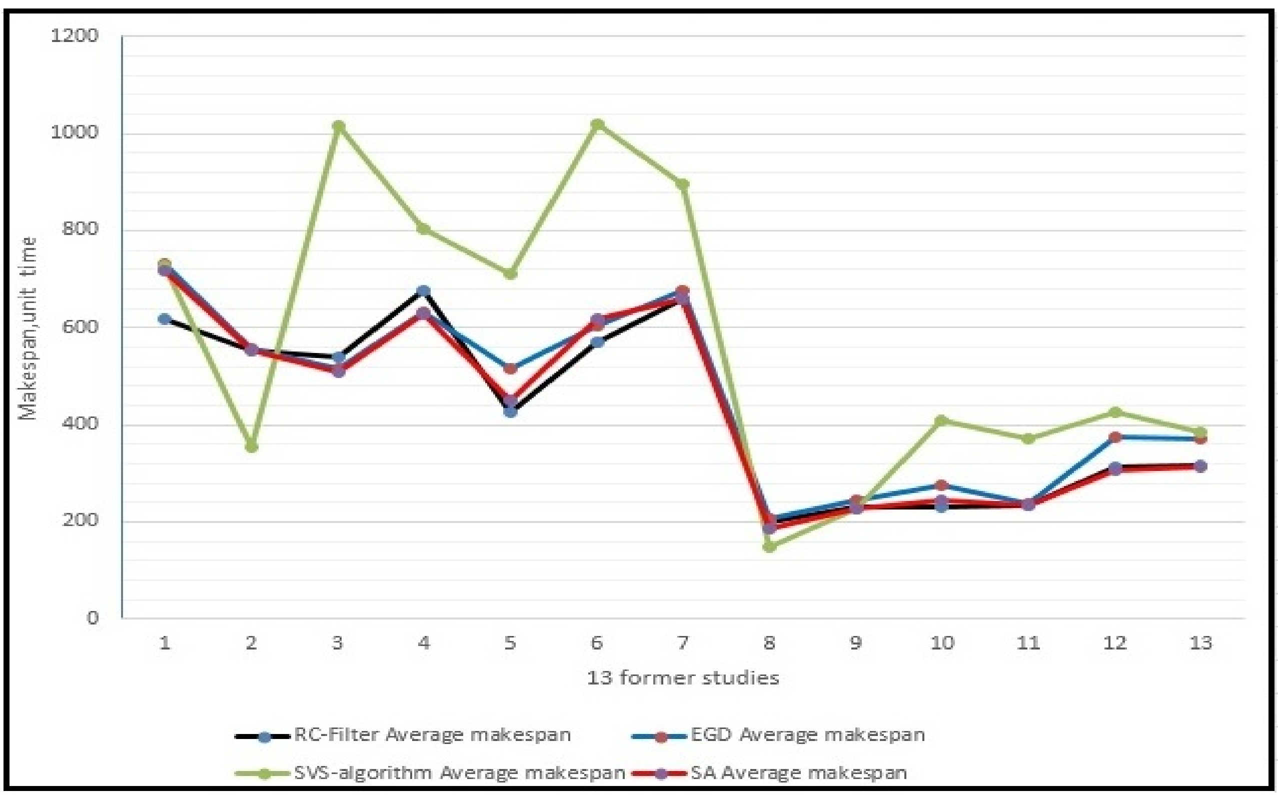

Figure 5.6 the graph chart shows the result obtained in table 5.9

5.12 Conclusion

In this paper, an optimization tool was proposed to optimize the sequence of parts, including EEs. The proposed tool was based on a dynamic manufacturing process. Two architectures were used, the first cell configuration was used for manufacturing EEs elements, and the second configuration was to come back to the original manufacturing cells to rework the rest of the tasks. The optimization of the sequence was validated by using a simulated annealing algorithm. The proposed approach was applied to a case study and compared with the RC-Filter approach. The obtained results were good at the level of the minimization of the makespan in each cell and at the level of the minimization of the inter-cell movement of exceptional elements. Moreover, the proposed approach was also applied to solve 13 scheduling problems adopted from previous researches. The results were compared to that given by RC-Filter, EGD algorithm, SVS-algorithm. In the majority of problems, the proposed tool gave better results than other published approaches, especially for large-size problems.

CONCLUSION, DISCUSSION AND FUTURE RESEARCH DIRECTIONS

This research explored state of the art in classical planning optimization. Important patterns and solutions were established, and findings were collected in an easily accessible manner. The flow out of materials and the layout of the facility design have a substantial effect on the performance of a manufacturing system. These two major elements can help to increase the production rate and reduce many negative elements such as work in process, inventory, setup time, and non-value added tasks. This advantage will help the business meets customer's requirements on time. Therefore, scheduling optimization would help to achieve huge benefits for the business itself. This research considers the cell scheduling problem in the attendance of the exceptional elements which cause inter-cellular movements in the Cellular manufacturing system. The Cellular Manufacturing System (CSM) reduces the cost of production & time; it also improves production flexibility. It divides the machine into distinctive parts and cells as per the manufacturing design and process. It is quite difficult to reduce the Makespan of manufacturing; it is known as the NP-Hard problem. For this problem, there is a metaheuristic methodology for optimal manufacturing scheduling and reducing the Makespan. There are several metaheuristics approaches under the CMS, namely, "Extended Great Deluge" (EGD), "Support Vector Scheduler" (SVS), and RC-Filter algorithms for the optimization of manufacturing scheduling and reducing the Makespan. Many researchers used the above-mentioned heuristic approaches in their studies to counter the NP-hard problem, optimize the job scheduling in the flow-line of cell manufacturing, optimize the parts' sequence, and reduce the Makespan. There are a lot of previously done researches, and their outcomes are discussed in this study to showcase the importance of CMS and Metaheuristic approaches. In this thesis, we have developed a strategy of scheduling by the use of a metaheuristic algorithm mathematical model in order to reduce the Makespan time required for manufacturing. There are several scheduling techniques discussed, including Open-Shop scheduling, Flow-Shop Scheduling, Job-Shop Scheduling. There are three parts of this thesis; in the first part, a metaheuristic algorithm known as RC-Filter is utilized to perform the optimization of manufacturing cell scheduling. The RC-Fitler is basically a simple filter that consists of the resistor (R) and a capacitor (C); it doesn't allow the signals with a higher amplitude to pass.

By using the RC-Filter metaheuristic approach, 13 different manufacturing scheduling problems obtained by previously done researches are experimented with. The result of this experimentation shown that 11 problems out of 13 are improved with their Makespan by 17% when the RC-Filter metaheuristic algorithm approach results compared with the previous results obtained by the EGD algorithm. While the RC-Filter results compared with the previously done experimentation with the EGD algorithm approach on the same problem, it showed ten problems are improved their Makespan by 44%. In addition to this, a case study is also used to check out the performance of the RC-Filter algorithm on a bigger problem. The selected cased study problem has 24 machines distributed into the seven cells to cause 40 parts. The selected manufacturing scheduling problem previously used the EGD algorithm technique. As the proposed RC-Filter algorithm approach was applied to the given big scheduling problem, their results showed an improvement of 4%. The second part of the thesis used a hybrid metaheuristic algorithm model, in which two approaches, namely "RC-Filter" and "Extended Great Deluge," are used together to overcome the NP-hard problem. The hybrid technique was also used by several researchers effectively in previous studies. The 13 selected problems from the literature, this time experimented with this approach, and the obtained results are compared with the previously obtained results of the same problems by using RC-Filter, SVS, and EGD approached individually. The results have shown that the hybrid metaheuristic approach has improved the error percentage by 71%. In this part, there is another case study problem experiment with the eight machines, seven cells, ten manufacturing parts, and four exceptional parts. The case study was already to study by the different researchers previously by using the SVG and EGD approaches. The results obtained by the proposed hybrid model, the Makespan improved by 35.9% as compared to the SVS algorithm and 10.7% when compared with the EGD algorithm. In the third part of this thesis, the "Simulated Annealing Meta-Heuristic" algorithm approach is used to optimize the manufacturing scheduling and reducing the Makespan. This approach has two stages, and each stage has two parts. In part 1 of stage 1, Exceptional Elements were optimized by using the original architecture of the cells via simulated annealing. The original cells were optimized as a job-shop problem because there were a lot of inter-cell movements. In part 2 of stage 1, the sequence in each cell was optimized. The first stage, characterized by these two parts, represented the first stage of this work with the aim of reducing the inter-cell movements used in a dynamic cell environment. In part 1 of stage 2, new cells were designed using the exceptional elements only. To do this task, the required machines used for the manufacturing of exceptional elements were moved to other cells. A specific cell's architecture was designed to handle exceptional elements. The aim of this part was to give a minimum of inter-cell movements and handling. In part 2 of stage 2, the configuration of the original cell was used, and the sequences of the parts were optimized in each cell. The optimization of the sequence of the parts was determined via the simulated annealing algorithm. This approach also experiments with all the pre-selected 13 manufacturing scheduling and Makespan problems. The results obtained from this study in the SA approach are compared with the results of previously done studies by using the RC-Filter, EGD, and SVS algorithm approach. The results are showing that 7 out of 13 problems showing the lowest Makespan for the proposed SA approach. Conclusively, all parts of this study were aiming for the same goal only, which is reducing the Makespan yet using different techniques & strategies to obtain it with different levels of precision.

The world is going advanced and adopting technology with the passage of each day, because of this, the requirement of the market is increasing day by day. In order to fulfill the requirement of the market, the manufacturing organizations should manufacture the products with more pace. So, it is the modern-day requirement for the manufacturing units to manufacture products at a higher pace, good quality, and low cost to meet the market competition. The manufacturing units have different manufacturing methods, but the most effective method is the “Cellular Manufacturing System” (CMS); it provides a high quality of product and has low production time. With the metaheuristic approaches, CMS is quite effective and efficient in today's manufacturing market. It reduces the Makespan time by grouping the machines into different cells for effective manufacturing. In this study, we also experimented with different metaheuristic algorithm approaches to check out their effects on the reduction in Makespan. This research has provided the potential efficiency of using a cellular manufacturing system with multiple products and taking advantage of the new technique of meta-heuristic in order to optimize the schedule in a manufacturing facility. This domain has a huge impact nowadays in the commercial market due to the rapidly and changeable competition between the manufacturing organizations and services organizations so that they can sustain in the market; otherwise, some of them will be out of business.

There is an unlimited research area, and directions related to scheduling optimization are open forever until the manual manufacturing revolution ends and becomes auto manufacturing. One of the open directions could be the locomotive facility layout to reduce the arrival time. Some limitations of the proposed approach, which require further research, are as follows. The considered cell scheduling problem can further be extended to include issues relating to material handling time, buffer size constraints, etc. One of the assumptions in the proposed cell scheduling model is that there is no backtracking within the manufacturing cells. Relaxation of this assumption can enhance the applicability of the proposed approach. Also, computer-aided design (CAD) is considered one of the most economical ways of saving time and money as a result of being a scheduling optimization method. There is another future research direction, morphing the control of the cell for "shop-wide production" control systems. In this technique, the software coordinates with the activity of the cell and performs the routing of pallet transporter to available machines, keeps monitoring on the work-in-progress and the machines. This system also has the ability to manage the production schedule.

In terms of the contributions of the work developed in this thesis, the Algorithm called RC-Filter was used in the first part of this thesis (in the first article) to solve the scheduling optimization problem using a cellular manufacturing system in order to minimize makespan as ultimate goal. A case study was presented to prove the algorithm's efficiency. In addition, this approach outperformed two previous algorithms EGD and SVS in former studies.
A combined two metaheuristics, the RC-Filter algorithm and the Extended Great Deluge (EGD), used in the second article were a beneficial proposal in this thesis to solve the problem of cellular manufacturing scheduling because, as indicated in the chapter 4, their performance was outstanding compared with other algorithms. Moreover, Simulating Annealing (SA) algorithm was applied for the first time in the third article to solve the optimization scheduling problem in the context of combination of two kinds of manufacturing systems, cellular and job shop and with the obtained results as showing in the chapter 5, we can say that the proposed approach is powerful.

LIMITATIONS

This research has used three different approaches, the RC- Filter algorithm, the hybrid of RC-Filter and EGD, and the SA algorithm, to optimize the sequence of the cells and the sequence of the parts in order to reduce the Makespan. However, there are many limitations to this research since it is a theoretical study. The limitations such as data collection; the data is obtained from the previously completed research under a similar domain. If the data was collected practically from the industry, so it can enhance the authenticity of our research. This research is also limited to the comparison with the research of previous studies. The results of our research are compared with the previously done research using RC-Filter, EGD, and SVS-algorithm. Each author of these previous studies used different computer capacity which affected the results. Other limitations like constraints such as setup time, metaheuristics mistakes during the search, workforce behaviour and more constraints.

A POTENTIAL INDUSTRIAL APPLICATION

The possibility of using the technique which had been applied in this thesis as cellular manufacturing system scheduling is very likely to be implemented smoothly in any small or medium size company of the multiproduct category production. There is a company in Montreal manufactured different parts used flow shop technique which it will be easy to implant the CMS concept to optimize its scheduling system and by the way, the manufacturing productivity.

LIST OF BIBLIOGRAPHICAL REFERENCES

Abdallah, B.M., Dao, T.-M., 2011. Optimization of group scheduling problem using the hybrid meta-heuristic extended great deluge (EGD) approach: a case study. Journal of Management & Engineering Integration 4, 1.

Ahmadian, M.M., Khatami, M., Salehipour, A., Cheng, T.C.E., 2021. Four decades of research on the open-shop scheduling problem to minimize the makespan. European Journal of Operational Research. https://doi.org/10.1016/j.ejor.2021.03.026

Ahmadian, M.M., Salehipour, A., Cheng, T.C.E., 2020. A meta-heuristic to solve the just-in-time job-shop scheduling problem. European Journal of Operational Research 288, 14–29. https://doi.org/10.1016/j.ejor.2020.04.017

Ai-Hua Yin, Wen-Qi Huang, 2002. A stochastic strategy for solving job shop scheduling problem, in: Proceedings. International Conference on Machine Learning and Cybernetics. Presented at the Proceedings. International Conference on Machine Learning and Cybernetics, pp. 434–439 vol.1. https://doi.org/10.1109/ICMLC.2002.1176791

Akhtar, M.U., Raza, M.H., Shafiq, M., 2019. Role of batch size in scheduling optimization of flexible manufacturing system using genetic algorithm. J Ind Eng Int 15, 135–146. https://doi.org/10.1007/s40092-018-0278-2

Akturk, M.S., 2011. Joint cell loading and scheduling approach to cellular manufacturing systems. International Journal of Production Research 49, 6321–6341. https://doi.org/10.1080/00207543.2010.532165

Alzidani, M., Dao, T.-M., 2019. Optimization of the cellular manufacturing scheduling using the RC-filter and EGD hybrid Meta-heuristics Approach. Int J Interact Des Manuf 13, 1549–1556. https://doi.org/10.1007/s12008-019-00562-x

Aminzadegan, S., Tamannaei, M., Rasti-Barzoki, M., 2019. Multi-agent supply chain scheduling problem by considering resource allocation and transportation. Computers & Industrial Engineering 137, 106003. https://doi.org/10.1016/j.cie.2019.106003

Arakawa, M., Fuyuki, M., Inoue, I., 2003. An optimization-oriented method for simulation-based job shop scheduling incorporating capacity adjustment function. International Journal of Production Economics, Structuring and Planning Operations 85, 359–369. https://doi.org/10.1016/S0925-5273(03)00122-1

Arikati, R., 2017. Multi-Criteria Flow-Shop Scheduling Optimization. Industrial and Manufacturing Engineering.

Asadzadeh, L., 2016. A parallel artificial bee colony algorithm for the job shop scheduling problem with a dynamic migration strategy. Computers & Industrial Engineering 102, 359–367. https://doi.org/10.1016/j.cie.2016.06.025

Asano, M., Ohta, H., 2002. A heuristic for job shop scheduling to minimize total weighted tardiness. Computers & Industrial Engineering 42, 137–147. https://doi.org/10.1016/S0360-8352(02)00019-0

Balabanov, T., Ivanov, S., Ketipov, R., 2020. Solving Combinatorial Puzzles with Parallel Evolutionary Algorithms. pp. 493–500. https://doi.org/10.1007/978-3-030-41032-2_56

Bekkar, A., Guemri, O., Aissani, N., 2016. An Iterative Greedy Insertion Technique for Flexible Job Shop Scheduling Problem. IFAC-PapersOnLine 49, 1956–1961. https://doi.org/10.1016/j.ifacol.2016.07.917

Bierwirth, C., Kuhpfahl, J., 2017. Extended GRASP for the job shop scheduling problem with total weighted tardiness objective. European Journal of Operational Research 261, 835–848. https://doi.org/10.1016/j.ejor.2017.03.030

Bilyk, A., Mönch, L., Almeder, C., 2014. Scheduling jobs with ready times and precedence constraints on parallel batch machines using metaheuristics. Computers & Industrial Engineering 78, 175–185. https://doi.org/10.1016/j.cie.2014.10.008

Burbidge, J.L., 1991. Production flow analysis for planning group technology. Journal of Operations Management 10, 5–27. https://doi.org/10.1016/0272-6963(91)90033-T

Çaliş, B., Bulkan, S., 2015. A research survey: review of AI solution strategies of job shop scheduling problem. J Intell Manuf 26, 961–973. https://doi.org/10.1007/s10845-013-0837-8

Calmels, D., 2019. The job sequencing and tool switching problem: state-of-the-art literature review, classification, and trends. International Journal of Production Research 57, 5005–5025. https://doi.org/10.1080/00207543.2018.1505057

Campbell, H.G., Dudek, R.A., Smith, M.L., 1970. A Heuristic Algorithm for the n Job, m Machine Sequencing Problem. Management Science 16, B-630. https://doi.org/10.1287/mnsc.16.10.B630

Chang, P.-C., Chen, S.-H., 2011. Integrating dominance properties with genetic algorithms for parallel machine scheduling problems with setup times. Applied Soft Computing 11, 1263–1274. https://doi.org/10.1016/j.asoc.2010.03.003

Chang, P.-C., Chen, S.-H., 2009. The development of a sub-population genetic algorithm II (SPGA II) for multi-objective combinatorial problems. Applied Soft Computing 9, 173–181. https://doi.org/10.1016/j.asoc.2008.04.002

Chang, P.-C., Chen, S.-H., Fan, C.-Y., Chan, C.-L., 2008a. Genetic algorithm integrated with artificial chromosomes for multi-objective flowshop scheduling problems. Applied Mathematics and Computation, Special Issue on Advanced Intelligent Computing Theory and Methodology in Applied Mathematics and Computation 205, 550–561. https://doi.org/10.1016/j.amc.2008.05.027

Chang, P.-C., Chen, S.-H., Fan, C.-Y., Mani, V., 2010. Generating artificial chromosomes with probability control in genetic algorithm for machine scheduling problems. Ann Oper Res 180, 197–211. https://doi.org/10.1007/s10479-008-0489-9

Chang, P.C., Chen, S.H., Mani, V., 2009. A hybrid genetic algorithm with dominance properties for single machine scheduling with dependent penalties. Applied Mathematical Modelling 33, 579–596. https://doi.org/10.1016/j.apm.2008.01.006

Chang, P.-C., Chen, S.-S., Fan, C.-Y., 2008b. Mining gene structures to inject artificial chromosomes for genetic algorithm in single machine scheduling problems. Applied Soft Computing 8, 767–777. https://doi.org/10.1016/j.asoc.2007.06.005

Chaudhry, I.A., Khan, A.A., 2016. A research survey: review of flexible job shop scheduling techniques. Intl. Trans. in Op. Res. 23, 551–591. https://doi.org/10.1111/itor.12199

Chen, H.J., Kacperczyk, M., Ortiz-Molina, H., 2011. Labor Unions, Operating Flexibility, and the Cost of Equity. J. Financ. Quant. Anal. 46, 25–58. https://doi.org/10.1017/S0022109010000645

Chen, S.-H., Chang, P.-C., Zhang, Q., Wang, C.-B., 2009. A guided memetic algorithm with probabilistic models. International Journal of Innovative Computing, Information and Control 5, 4753–4764.

Chou, F.-D., 2013. Particle swarm optimization with cocktail decoding method for hybrid flow shop scheduling problems with multiprocessor tasks. International Journal of Production Economics 141, 137–145. https://doi.org/10.1016/j.ijpe.2012.05.015

Cortez, P.M.C., Costa, A.M., 2015. Sequencing mixed-model assembly lines operating with a heterogeneous workforce. International Journal of Production Research 53, 3419–3432. https://doi.org/10.1080/00207543.2014.987881

Dai, M., Tang, D., Xu, Y., Li, W., 2015. Energy-aware integrated process planning and scheduling for job shops. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture 229, 13–26. https://doi.org/10.1177/0954405414553069

Das, S., Dash, H.R., 2014. Microbial Bioremediation, in: Microbial Biodegradation and Bioremediation. Elsevier, pp. 1–21. https://doi.org/10.1016/B978-0-12-800021-2.00001-7

Demir, Y., İşleyen, S.K., 2014. An effective genetic algorithm for flexible job-shop scheduling with overlapping in operations. International Journal of Production Research 52, 3905–3921. https://doi.org/10.1080/00207543.2014.889328

Dennie, J., 2006. Efficient job scheduling for a cellular manufacturing environment.

Dorigo, M., Dorigo, D. de R.D.F.M., Stützle, T., 2004. Ant Colony Optimization. MIT Press.

Eren, Y., Küçükdemiral, İ.B., Üstoğlu, İ., 2017. Introduction to Optimization, in: Optimization in Renewable Energy Systems. Elsevier, pp. 27–74. https://doi.org/10.1016/B978-0-08-101041-9.00002-8

Fletcher, R., Powell, M.J.D., 1963. A Rapidly Convergent Descent Method for Minimization. Comput J 6, 163–168. https://doi.org/10.1093/comjnl/6.2.163

Gaafar, L.K., Masoud, S.A., 2005a. Genetic algorithms and simulated annealing for scheduling in agile manufacturing. International Journal of Production Research 43, 3069–3085. https://doi.org/10.1080/00207540412331333414

Gaafar, L.K., Masoud, S.A., 2005b. Genetic algorithms and simulated annealing for scheduling in agile manufacturing. International Journal of Production Research 43, 3069–3085. https://doi.org/10.1080/00207540412331333414

Gansterer, M., Almeder, C., Hartl, R.F., 2014. Simulation-based optimization methods for setting production planning parameters. International Journal of Production Economics 151, 206–213. https://doi.org/10.1016/j.ijpe.2013.10.016

GFG, 2020. Difference between NP hard and NP complete problem. GeeksforGeeks. URL https://www.geeksforgeeks.org/difference-between-np-hard-and-np-complete-problem/ (accessed 4.3.21).

Godinho Filho, M., Barco, C.F., Tavares Neto, R.F., 2014. Using Genetic Algorithms to solve scheduling problems on flexible manufacturing systems (FMS): a literature survey, classification and analysis. Flex Serv Manuf J 26, 408–431. https://doi.org/10.1007/s10696-012-9143-6

Golenko-Ginzburg, D., Gonik, A., 2002. Optimal job-shop scheduling with random operations and cost objectives. International Journal of Production Economics 76, 147–157. https://doi.org/10.1016/S0925-5273(01)00140-2

Gonçalves, J.F., Mendes, J.J.M., Resende, M.G.C., 2008. A genetic algorithm for the resource constrained multi-project scheduling problem. European Journal of Operational Research 189, 1171–1190. https://doi.org/10.1016/j.ejor.2006.06.074

Grothklags, S., Streit, A., 2004. On the comparison of CPLEX-computed job schedules with the self-tuning dynP job scheduler, in: 18th International Parallel and Distributed Processing Symposium, 2004. Proceedings. Presented at the 18th International Parallel and Distributed Processing Symposium, 2004. Proceedings., pp. 250-. https://doi.org/10.1109/IPDPS.2004.1303310

Guo, C., Zhibin, J., Zhang, H., Li, N., 2012. Decomposition-based classified ant colony optimization algorithm for scheduling semiconductor wafer fabrication system. Computers & Industrial Engineering 62, 141–151. https://doi.org/10.1016/j.cie.2011.09.002

Ham, I., Hitomi, K., Yoshida, T., 2012. Group technology: applications to production management. Springer Science & Business Media.

Harrath, Y., Chebel-Morello, B., Zerhouni, N., 2002. A genetic algorithm and data mining based meta-heuristic for job shop scheduling problem, in: IEEE International Conference on Systems, Man and Cybernetics. Presented at the IEEE International Conference on Systems, Man and Cybernetics, p. 6 pp. vol.7-. https://doi.org/10.1109/ICSMC.2002.1175709

Hazaras, M.J., Swartz, C.L.E., Marlin, T.E., 2012. Flexible maintenance within a continuous-time state-task network framework. Computers & Chemical Engineering 46, 167–177. https://doi.org/10.1016/j.compchemeng.2012.06.028

Hitomi, K., Ham, I., 1976. Operations scheduling for group technology applications. Annals of the CIRP 25, 419–422.

Huang, K.-L., Liao, C.-J., 2008. Ant colony optimization combined with taboo search for the job shop scheduling problem. Computers & Operations Research 35, 1030–1046. https://doi.org/10.1016/j.cor.2006.07.003

Hyer, N.L., Wemmerlov, U., 2002. The office that lean built: applying cellular thinking to administrative work. IIE Solutions 34, 37–45.

Jalalian, M.M., 2018. Application of Metaheuristics in Scheduling Continuous/Semi-continuous Process Industries and a Case Study (PhD Thesis).

Janis, A., Bade, A., 2016. Path Planning Algorithm in Complex Environment: A Survey. Transactions on Science and Technology 3, 31–40.

Jat, S.N., Yang, S., 2011. A hybrid genetic algorithm and tabu search approach for post enrolment course timetabling. J Sched 14, 617–637. https://doi.org/10.1007/s10951-010-0202-0

Kaplanoğlu, V., 2016. An object-oriented approach for multi-objective flexible job-shop scheduling problem. Expert Systems with Applications 45, 71–84. https://doi.org/10.1016/j.eswa.2015.09.050

Khalid, Q.S., Arshad, M., Maqsood, S., Jahanzaib, M., Babar, A.R., Khan, I., Mumtaz, J., Kim, S., 2019. Hybrid Particle Swarm Algorithm for Products' Scheduling Problem in Cellular Manufacturing System. Symmetry 11, 729. https://doi.org/10.3390/sym11060729

Kia, R., Baboli, A., Javadian, N., Tavakkoli-Moghaddam, R., Kazemi, M., Khorrami, J., 2012. Solving a group layout design model of a dynamic cellular manufacturing system with alternative process routings, lot splitting and flexible reconfiguration by simulated annealing. Computers & Operations Research 39, 2642–2658. https://doi.org/10.1016/j.cor.2012.01.012

Kim, G.H., Lee, C.S.G., 1994. An evolutionary approach to the job-shop scheduling problem, in: Proceedings of the 1994 IEEE International Conference on Robotics and Automation. Presented at the Proceedings of the 1994 IEEE International Conference on Robotics and Automation, pp. 501–506 vol.1. https://doi.org/10.1109/ROBOT.1994.351249

Kirkpatrick, S., Gelatt, C.D., Vecchi, M.P., 1983. Optimization by Simulated Annealing. Science 220, 671–680. https://doi.org/10.1126/science.220.4598.671

Kis, T., 2003. Job-shop scheduling with processing alternatives. European Journal of Operational Research, Meta-heuristics in combinatorial optimization 151, 307–332. https://doi.org/10.1016/S0377-2217(02)00828-7

Korytkowski, P., Wiśniewski, T., Rymaszewski, S., 2013. An evolutionary simulation-based optimization approach for dispatching scheduling. Simulation Modelling Practice and Theory 35, 69–85. https://doi.org/10.1016/j.simpat.2013.03.006

Koulamas, C., Panwalkar, S.S., 2016. The proportionate two-machine no-wait job shop scheduling problem. European Journal of Operational Research 252, 131–135. https://doi.org/10.1016/j.ejor.2016.01.010

Krajewski, 2007. Operations Management: Processes And Value Chains, 8/E. Pearson Education, India.

Krishna, C., n.d. Production Planning & Control | Scheduling.

Kumar, D.A., Ramesh, V., 2012. Cellular Manufacturing Layout Design in Inner Tube Manufacturing Industry: A Case Study. Published in International Journal of Scientific Engineering and Technology Volume 306–313.

Kumar, K.R., Vannelli, A., 1986. Strategic subcontracting for efficient disaggregated manufacturing.

Lengyel, A., Hatono, I., Ueda, K., 2003. Scheduling for on-time completion in job shops using feasibility function. Computers & Industrial Engineering 45, 215–229. https://doi.org/10.1016/S0360-8352(03)00042-1

Li, X., Gao, L., 2016. An effective hybrid genetic algorithm and tabu search for flexible job shop scheduling problem. International Journal of Production Economics 174, 93–110. https://doi.org/10.1016/j.ijpe.2016.01.016

Liang, X., Huang, M., Ning, T., 2018. Flexible job shop scheduling based on improved hybrid immune algorithm. J Ambient Intell Human Comput 9, 165–171. https://doi.org/10.1007/s12652-016-0425-9

Liang, Y.-C., Hsiao, Y.-M., Tien, C.-Y., 2013. Metaheuristics for drilling operation scheduling in Taiwan PCB industries. International Journal of Production Economics, Meta-heuristics for manufacturing scheduling and logistics problems 141, 189–198. https://doi.org/10.1016/j.ijpe.2012.04.014

Liao, C.-J., Gen, M., Tiwari, M.K., Chang, P.-C., 2013. Meta-heuristics for manufacturing scheduling and logistics problems. International Journal of Production Economics, Meta-heuristics for manufacturing scheduling and logistics problems 141, 1–3. https://doi.org/10.1016/j.ijpe.2012.09.004

Liao, C.-J., Liao, L.-M., 2008. Improved MILP models for two-machine flowshop with batch processing machines. Mathematical and Computer Modelling 48, 1254–1264. https://doi.org/10.1016/j.mcm.2008.01.001

Liao, T.W., Egbelu, P.J., Chang, P.C., 2013. Simultaneous dock assignment and sequencing of inbound trucks under a fixed outbound truck schedule in multi-door cross docking operations. International Journal of Production Economics, Meta-heuristics for manufacturing scheduling and logistics problems 141, 212–229. https://doi.org/10.1016/j.ijpe.2012.03.037

Lin, L., Gen, M., Wang, X., 2009. Integrated multistage logistics network design by using hybrid evolutionary algorithm. Computers & Industrial Engineering, Intelligent Manufacturing and Logistics 56, 854–873. https://doi.org/10.1016/j.cie.2008.09.037

Liou, C.-D., Hsieh, Y.-C., Chen, Y.-Y., 2013. A new encoding scheme-based hybrid algorithm for minimising two-machine flow-shop group scheduling problem. International Journal of Systems Science 44, 77–93. https://doi.org/10.1080/00207721.2011.581396

Liou, C.-D., Liu, C.-H., 2010. A Novel Encoding Scheme of PSO for Two-Machine Group Scheduling, in: Tan, Y., Shi, Y., Tan, K.C. (Eds.), Advances in Swarm Intelligence, Lecture Notes in Computer Science. Springer, Berlin, Heidelberg, pp. 128–134. https://doi.org/10.1007/978-3-642-13495-1_16

Logendran, R., Nudtasomboon, N., 1991. Minimizing the makespan of a group scheduling problem: a new heuristic. International Journal of Production Economics 22, 217–230. https://doi.org/10.1016/0925-5273(91)90098-E

Mati, Y., Xiaolan Xie, 2003. A polynomial algorithm for a two-job shop scheduling problem with routing flexibility, in: 2003 IEEE International Conference on Robotics and Automation (Cat. No.03CH37422). Presented at the 2003 IEEE International Conference on Robotics and Automation (Cat. No.03CH37422), pp. 157–162 vol.1. https://doi.org/10.1109/ROBOT.2003.1241589

Mattfeld, D.C., Bierwirth, C., 2004. An efficient genetic algorithm for job shop scheduling with tardiness objectives. European Journal of Operational Research, Traffic and Transportation Systems Analysis 155, 616–630. https://doi.org/10.1016/S0377-2217(03)00016-X

McCollum, B., McMullan, P., Parkes, A.J., Burke, E.K., Abdullah, S., 2009. An extended great deluge approach to the examination timetabling problem. Proceedings of the 4th multidisciplinary international scheduling: Theory and applications 2009 (MISTA 2009) 424–434.

Mihoubi, B., Bouzouia, B., Gaham, M., 2020. Reactive scheduling approach for solving a realistic flexible job shop scheduling problem. International Journal of Production Research 0, 1–19. https://doi.org/10.1080/00207543.2020.1790686

Ming Wut, T., Chou, T., 2009. Children's influences on family decision making in Hong Kong. Young Consumers 10, 146–156. https://doi.org/10.1108/17473610910964723

Miyashita, T., 2003. An application of immune algorithms for job-shop scheduling problems, in: Proceedings of the IEEE International Symposium OnAssembly and Task Planning, 2003. Presented at the Proceedings of the IEEE International Symposium onAssembly and Task Planning, 2003., pp. 146–150. https://doi.org/10.1109/ISATP.2003.1217202

Mohammadi, M., Forghani, K., 2017. A hybrid method based on genetic algorithm and dynamic programming for solving a bi-objective cell formation problem considering alternative process routings and machine duplication. Applied Soft Computing 53, 97–110. https://doi.org/10.1016/j.asoc.2016.12.039

Mosbah, A.B., Botez, R.M., Dao, T.-M., 2016. New methodology combining neural network and extended great deluge algorithms for the ATR-42 wing aerodynamics analysis. The Aeronautical Journal 120, 1049–1080. https://doi.org/10.1017/aer.2016.46

Nahas, N., Nourelfath, M., 2014. Nonlinear threshold accepting meta-heuristic for combinatorial optimisation problems. International Journal of Metaheuristics 3, 265–290. https://doi.org/10.1504/IJMHEUR.2014.068904

Neufeld, J.S., Teucher, F.F., Buscher, U., 2019. Scheduling flowline manufacturing cells with inter-cellular moves: non-permutation schedules and material flows in the cell scheduling problem. International Journal of Production Research 1–17. https://doi.org/10.1080/00207543.2019.1683251

Nomden, G., Slomp, J., 2006. The applicability of cellular manufacturing techniques: an exploration in industry, in: Proceedings of the Third International Conference on Group Technology/Cellular Manufacturing, Groningen. pp. 287–296.

Ohmae, H., Ikkai, Y., Komoda, N., Horiuchi, K., Hamamoto, H., 2003. A high speed scheduling method by analyzing job flexibility and taboo search for a large-scale job shop problem with group constraints, in: EFTA 2003. 2003 IEEE Conference on Emerging Technologies and Factory Automation. Proceedings (Cat. No.03TH8696). Presented at the EFTA 2003. 2003 IEEE Conference on Emerging Technologies and Factory Automation. Proceedings (Cat. No.03TH8696), pp. 227–232 vol.2. https://doi.org/10.1109/ETFA.2003.1248704

Öztop, H., Tasgetiren, M.F., Eliiyi, D.T., Pan, Q.-K., Kandiller, L., 2020. An energy-efficient permutation flowshop scheduling problem. Expert Systems with Applications 150, 113279. https://doi.org/10.1016/j.eswa.2020.113279

PAC, 2012. Lean Cellular Manufacturing: Processing, Methods, Layouts, and Implementation. Production Automation Station. URL https://blog.gotopac.com/2012/04/24/cellular-manufacturing/ (accessed 4.10.21).

Pang, K.-W., 2013. A genetic algorithm based heuristic for two machine no-wait flowshop scheduling problems with class setup times that minimizes maximum lateness. International Journal of Production Economics, Meta-heuristics for manufacturing scheduling and logistics problems 141, 127–136. https://doi.org/10.1016/j.ijpe.2012.06.017

Papaioannou, G., Wilson, J.M., 2010. The evolution of cell formation problem methodologies based on recent studies (1997–2008): Review and directions for future research. European Journal of Operational Research 206, 509–521. https://doi.org/10.1016/j.ejor.2009.10.020

Park, J., Nguyen, S., Zhang, M., Johnston, M., 2015. Evolving Ensembles of Dispatching Rules Using Genetic Programming for Job Shop Scheduling, in: Machado, P., Heywood, M.I., McDermott, J., Castelli, M., García-Sánchez, P., Burelli, P., Risi, S., Sim, K. (Eds.), Genetic Programming, Lecture Notes in Computer Science. Springer International Publishing, Cham, pp. 92–104. https://doi.org/10.1007/978-3-319-16501-1_8

Pasupathy, T., Rajendran, C., Suresh, R.K., 2006. A multi-objective genetic algorithm for scheduling in flow shops to minimize the makespan and total flow time of jobs. Int J Adv Manuf Technol 27, 804–815. https://doi.org/10.1007/s00170-004-2249-6

Patkai, B., Torvinen, S., 1999. Job-shop scheduling with a combination of evolutionary and heuristic methods, in: Intelligent Systems in Design and Manufacturing II. Presented at the Intelligent Systems in Design and Manufacturing II, International Society for Optics and Photonics, pp. 54–62. https://doi.org/10.1117/12.359504

Rahmani Hosseinabadi, A.A., Vahidi, J., Saemi, B., Sangaiah, A.K., Elhoseny, M., 2019. Extended Genetic Algorithm for solving open-shop scheduling problem. Soft Comput 23, 5099–5116. https://doi.org/10.1007/s00500-018-3177-y

Shukla, N., Choudhary, A.K., Prakash, P.K.S., Fernandes, K.J., Tiwari, M.K., 2013. Algorithm portfolios for logistics optimization considering stochastic demands and mobility allowance. International Journal of Production Economics, Meta-heuristics for manufacturing scheduling and logistics problems 141, 146–166. https://doi.org/10.1016/j.ijpe.2012.07.007

Shukla, O.J., Soni, G., Kumar, R., A, S., 2018. An agent-based architecture for production scheduling in dynamic job-shop manufacturing system. at - Automatisierungstechnik 66, 492–502. https://doi.org/10.1515/auto-2017-0119

Solimanpur, M., Vrat, P., Shankar, R., 2004. A heuristic to minimize makespan of cell scheduling problem. International Journal of Production Economics 88, 231–241. https://doi.org/10.1016/S0925-5273(03)00196-8

Sridhar, J., Rajendran, C., 1996. Scheduling in flowshop and cellular manufacturing systems with multiple objectives— a genetic algorithmic approach. Production Planning & Control 7, 374–382. https://doi.org/10.1080/09537289608930365

Sridhar, J., Rajendran, C., 1994. A genetic algorithm for family and job scheduling in a flowline-based manufacturing cell. Computers & Industrial Engineering, 16th Annual Conference on Computers and Industrial Engineering 27, 469–472. https://doi.org/10.1016/0360-8352(94)90336-0

Sridhar, J., Rajendran, C., 1993. Scheduling in a cellular manufacturing system: a simulated annealing approach. International Journal of Production Research 31, 2927–2945. https://doi.org/10.1080/00207549308956908

Subhaa, R., Jawahar, N., Ponnambalam, S.G., 2019. An improved design for cellular manufacturing system associating scheduling decisions. Sādhanā 44, 155. https://doi.org/10.1007/s12046-019-1135-8

Supsomboon, S., Vajasuvimon, A., 2016. Simulation model for job shop production process improvement in machine parts manufacturing. International Journal of Simulation Modelling 15, 611–622.

Suzić, N., Stevanov, B., Ćosić, I., Anišić, Z., Sremčev, N., 2012. Customizing products through application of group technology: A case study of furniture manufacturing. Strojniški vestnik-Journal of Mechanical Engineering 58, 724–731.

Swarnkar, R., Tiwari, M.K., 2004. Modeling machine loading problem of FMSs and its solution methodology using a hybrid tabu search and simulated annealing-based heuristic approach. Robotics and Computer-Integrated Manufacturing 20, 199–209. https://doi.org/10.1016/j.rcim.2003.09.001

TEIM, 2010. Product Flow [WWW Document]. URL http://www.teiminc.com/product_flow.htm (accessed 4.10.21).

Thiagarajan, S., Rajendran, C., 2005. Scheduling in dynamic assembly job-shops to minimize the sum of weighted earliness, weighted tardiness and weighted flowtime of jobs. Computers & Industrial Engineering 49, 463–503. https://doi.org/10.1016/j.cie.2005.06.005

Thiruvady, D., Singh, G., Ernst, A.T., Meyer, B., 2013. Constraint-based ACO for a shared resource constrained scheduling problem. International Journal of Production Economics, Meta-heuristics for manufacturing scheduling and logistics problems 141, 230–242. https://doi.org/10.1016/j.ijpe.2012.06.012

Tseng, C.-T., Liao, C.-J., 2008a. A particle swarm optimization algorithm for hybrid flow-shop scheduling with multiprocessor tasks. International Journal of Production Research 46, 4655–4670. https://doi.org/10.1080/00207540701294627

Tseng, C.-T., Liao, C.-J., 2008b. A discrete particle swarm optimization for lot-streaming flowshop scheduling problem. European Journal of Operational Research 191, 360–373. https://doi.org/10.1016/j.ejor.2007.08.030

Tsujimura, Y., Mafune, Y., Gen, M., 2000. Introducing co-evolution and sub-evolution processes into genetic algorithm for job-shop scheduling, in: 2000 26th Annual Conference of the IEEE Industrial Electronics Society. IECON 2000. 2000 IEEE International Conference on Industrial Electronics, Control and Instrumentation. 21st Century Technologies. Presented at the 2000 26th Annual Conference of the IEEE Industrial Electronics Society. IECON 2000. 2000 IEEE International Conference on Industrial Electronics, Control and Instrumentation. 21st Century Technologies, pp. 2827–2830 vol.4. https://doi.org/10.1109/IECON.2000.972446

Voß, S., 2009. Metaheuristics, in: Floudas, C.A., Pardalos, P.M. (Eds.), Encyclopedia of Optimization. Springer US, Boston, MA, pp. 2061–2075. https://doi.org/10.1007/978-0-387-74759-0_367

Wemmerlov, U., Hyer, N., 1989. Cellular manufacturing in the U.S. industry: a survey of users. International Journal of Production Research 27, 1511–1530. https://doi.org/10.1080/00207548908942637

Wu, T.-H., Chung, S.-H., Chang, C.-C., 2009. Hybrid simulated annealing algorithm with mutation operator to the cell formation problem with alternative process routings. Expert Systems with Applications 36, 3652–3661. https://doi.org/10.1016/j.eswa.2008.02.060

Wu, X., Chu, C.-H., Wang, Y., Yue, D., 2007. Genetic algorithms for integrating cell formation with machine layout and scheduling. Computers & Industrial Engineering, Selected Papers from The 27th. International Conference on Computers & Industrial Engineering - Part 2 53, 277–289. https://doi.org/10.1016/j.cie.2007.06.021

Xu, L., Qiu, Z., Kang, Z., Ma, X., Xiong, H., Yang, L., 2020. Time-window-based Scheduling Strategy and Optimization for Maximizing the Income of Drop and Pull Transport, in: IOP Conference Series: Materials Science and Engineering. IOP Publishing, p. 012074.

Yazdani, M., Aleti, A., Khalili, S.M., Jolai, F., 2017. Optimizing the sum of maximum earliness and tardiness of the job shop scheduling problem. Computers & Industrial Engineering 107, 12–24. https://doi.org/10.1016/j.cie.2017.02.019

Yunpeng Pan, Leyuan Shi, 2005. Dual constrained single machine sequencing to minimize total weighted completion time. IEEE Transactions on Automation Science and Engineering 2, 344–357. https://doi.org/10.1109/TASE.2005.853474

Zabihi, S., Rashidi Kahag, M., Maghsoudlou, H., Afshar-Nadjafi, B., 2019. Multi-objective teaching-learning-based meta-heuristic algorithms to solve multi-skilled project scheduling problem. Computers & Industrial Engineering 136, 195–211. https://doi.org/10.1016/j.cie.2019.07.032

Zhang, R., Song, S., Wu, C., 2013. A hybrid artificial bee colony algorithm for the job shop scheduling problem. International Journal of Production Economics, Meta-heuristics for manufacturing scheduling and logistics problems 141, 167–178. https://doi.org/10.1016/j.ijpe.2012.03.035

Zhou, H., Feng, Y., Han, L., 2001. The hybrid heuristic genetic algorithm for job shop scheduling. Computers & Industrial Engineering 40, 191–200. https://doi.org/10.1016/S0360-8352(01)00017-1

Zhou, Y., Guo, S., Xu, F., Cui, D., Ge, W., Chen, X., Gu, B., 2020. Multi-Time Scale Optimization Scheduling Strategy for Combined Heat and Power System Based on Scenario Method. Energies 13, 1599. https://doi.org/10.3390/en13071599

Zhu, H., Chen, M., Zhang, Z., Tang, D., 2019. An Adaptive Real-Time Scheduling Method for Flexible Job Shop Scheduling Problem With Combined Processing Constraint. IEEE Access 7, 125113–125121. https://doi.org/10.1109/ACCESS.2019.2938548

Zolfaghari, S., Liang, M., 1999. Jointly solving the group scheduling and machining speed selection problems: A hybrid tabu search and simulated annealing approach. International Journal of Production Research 37, 2377–2397. https://doi.org/10.1080/002075499190815