ENERGY-AWARE FLEXIBLE JOB SHOP SCHEDULING PROBLEM AND PREVENTIVE MAINTENANCE UNDER THE LIMITED RESOURCE CONSTRAINTS

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A thesis

presented to Ryerson University

in partial fulfillment of the

requirements for the degree of

Master of Applied Science

in the program of

Mechanical and Industrial Engineering

Toronto, Ontario, Canada, 2020

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Master of Applied Science, 2020,
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ABSTRACT

This thesis presents the development of a novel model for solving the flexible job shop scheduling problem with maintenance activities where maintenance activities are limited by a maintenance crew constraint. Moreover, in order to extend it in terms of energy consumption, the cost of energy usage associated with different states of the machines is considered in the objective function. The objective is to minimize the total cost of hiring repairmen, energy consumption, and tardiness penalties. We assume the production machines in this environment may break down which causes the unavailability of the machines for the production. In the maintenance phase, a threshold-based maintenance strategy is applied based on the obtained optimal replacement age of each machine. Accordingly, the required maintenance action is divided into two categories: minimal repair or replacement activities. Furthermore, opportunistic maintenance is considered in the scheduling to minimize the required number of repairmen to be hired. In fact, the main aims are to find the optimal machine assignment and operation sequence, to determine if preventive maintenance is required to be executed between two consecutive operations, and to specify the optimal number of maintenance crew to be hired for the shop floor to minimize the expected total cost.

ACKNOWLEDGEMENTS

I would like to thank my dedicated parents and my brother for their unqualified support. They have always been encouraging to me. Without their help and inspiration, I would never have gotten to be at this point of my development. I honor them, and I owe them my entire life.

I would like to express my deepest gratitude to my supervisor, Dr. Sharareh Taghipour for her immense support and guidance during my graduate study. Dr. Taghipour has always been encouraging, supportive, and understanding. I learned a lot from her since she introduced me to a new and applicable field of production planning and maintenance. I dedicate this thesis to her for giving me this life-changing experience.

Special thanks go to Professor Ghasempoor, Associate Chair of the MIE Department for his professional guidance, unbiased comments, and words of wisdom. He has inspired and has been personally supportive of me and, overall, he has tirelessly worked with international students to achieve their goals. We appreciate his efforts.

I would also like to thank my dear friend, Mageed Ghaleb, for his invaluable company and support. He introduced me to other insights in my research area. I dedicate this thesis to honor our friendship.

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1. INTRODUCTION

1.1 Production scheduling

Scheduling can be described as the dedication of resources to execute a set of tasks within a designated period of time. In fact, scheduling is a decision-making procedure that is used in industries to plan their manufacturing activities appropriately, in a way that optimization can be conducted on specific performance metrics. Planning an efficient schedule plays a paramount role in production systems since it leads to reduction of cost, increase in productivity, customer satisfaction and competitive advantage (Sharma, Sharma, & Sharma, 2018). From production scheduling points of view, the resources and tasks are generally defined as machines and jobs (Özgüven, Özbakir, & Yavuz, 2010). There are varied types of production scheduling, including single machine, parallel machines, flow-shop or job shop. For each one, different scheduling rules and machines configuration are defined to plan production tasks over the machines (Hadidi, Turki, & Rahim, 2012). Machine configuration is determined based on the requirement of a manufacturing process, product prerequisites, and machine shops (Amjad et al., 2018). Figure 1 depicts a schematic classification of machine layouts.

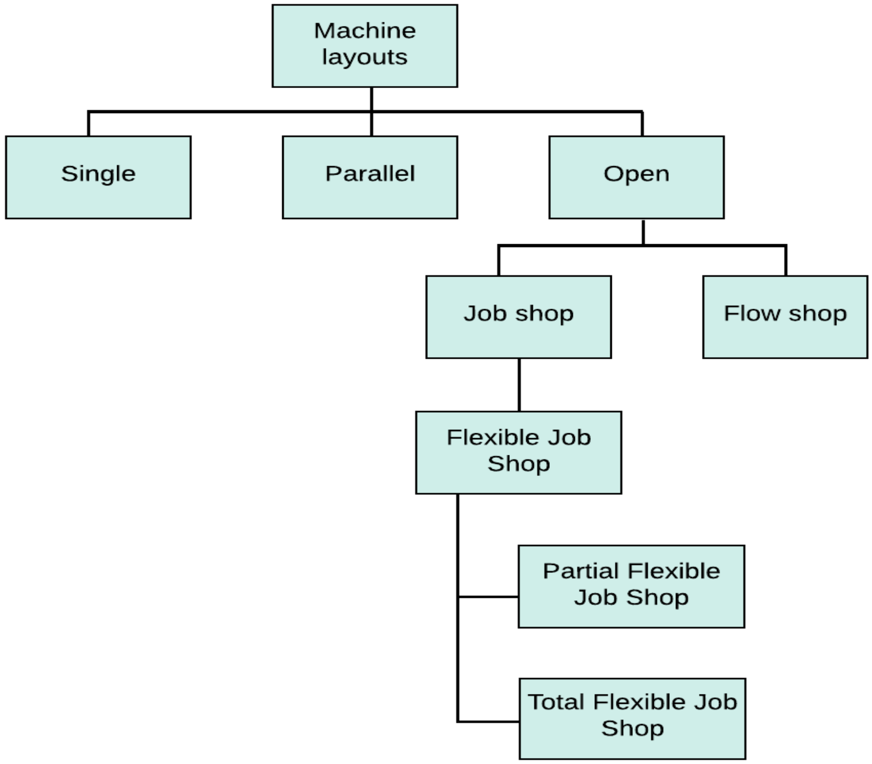

Figure 1.1 Classification of shop layouts (Amjad et al., 2018)

Almost all scheduling problems are generally recognized as complex combinatorial optimization problems that involve a set of constraints. Some of these constraints are the precedence, due date, and resource availability. As such, this problem has attained the growing attention of researchers since the early 1950s because of increasing competition in markets (Özgüven et al., 2010).

1.1.1 Single-machine

Single machine layout is the simplest schedule in comparison to other machine configurations. Basically, single machine scheduling deals with sequencing a series of jobs on a single machine in order to optimize one or more performance measures. The performance measures include (lee chung yee, lei lei, & michael pinedo, 1997):

- Makespan (C_{max}): The makespan refers to the time that all the assigned jobs to be completed and leave the shop floor. The least possible makespan indicates an efficient usage of the machines which is the most common objective for scheduling problems.
- Lateness (L): In scheduling, the lateness of the job refers to the violation of the given due date.
- Tardiness (T): In scheduling, tardiness is typically a measure of a delay in the completion time of the jobs in the shop floor. The difference between the completion time and the due date of the given job represents tardiness.

Both lateness and tardiness are related to the due date, but tardiness cannot be negative. In practice, the obtained results for single-machine models provide a basis for the complicated machine configurations.

1.1.2 Parallel-machine

In the parallel-machine layout, each job requires a single operation to be processed on one of *m* machines, which are placed in parallel. The parallel-machine scheduling problems have been widely applied in the machinery, textile, chemical, electronics manufacturing, plastics forming, and service industries (S. Lin, Lu, & Ying, 2011). Figure 1.2 shows a parallel system consisting of *n* jobs and *m* machines.

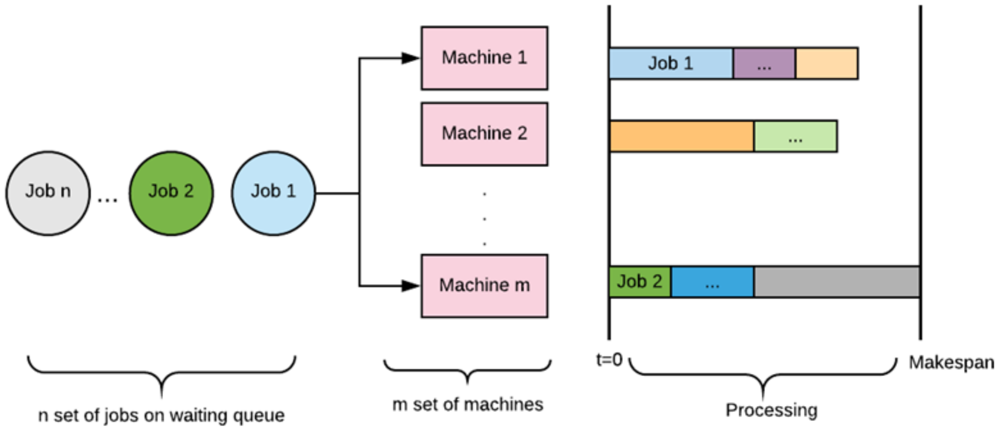

Figure 1.2 Schematic representation of parallel-machine scheduling

Based on the characteristics of parallel machines, this scheduling problem is categorized into three types as:

1. Identical parallel-machine: All machines are similar and they have the same characteristics.
2. Uniform parallel-machine: Each machine has various processing speeds for all jobs.
3. Unrelated parallel-machine: The processing times of the jobs depend on the machine to which they are assigned and there is no predefined rule of the processing times of these jobs.

1.1.3 Flow shops

The flow shop (FS) scheduling problem is finding a sequence of a set of jobs on a set of machines with the same order in order to optimize certain performance measure(s) (Mutlu & Yagmahan, 2014) as illustrated in Figure 1.3. This Figure shows a FS system consisting of *n* jobs and *m* machines where jobs are processed on each machine in the same order. Every job has to be operated on each machine once.

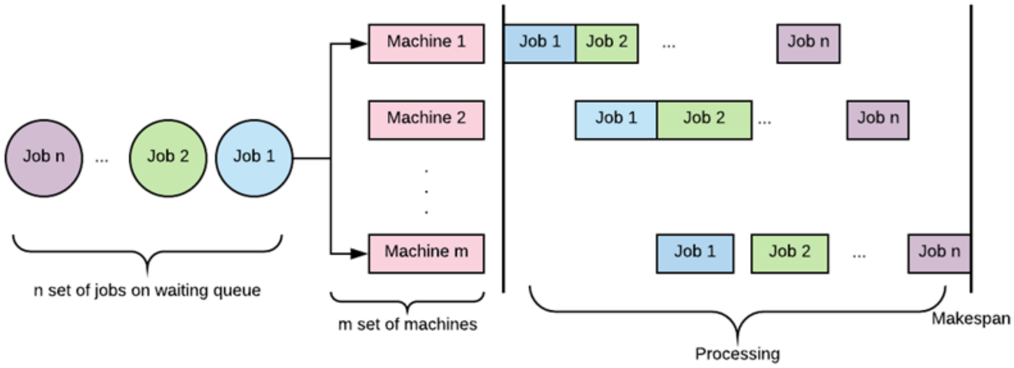

Figure 1.3 Flow shop scheduling problem with m machines and n jobs

In fact, this system is believed to work under the “First In First Out” (FIFO) method. In practice, FS structure has been employed in some industrial areas such as drug manufacturers (Chandra, Mehta, & Tirupati, 2009) and automotive manufacturing companies(J. Xu & Zhou, 2009). Figure 1.4 delineates part of a production line at the Geely manufacturing industry.

Figure 1.4 An application to flow-shop scheduling at GEELY company in China (https://en.wikipedia.org/wiki/Automotive_industry)

1.1.4 Job shops

Job shops are prevalent in many production systems. In the classical JSP, each job includes a sequence of successive operations which are processed by a set of machines. The JSP functions only on one available machine for each operation and the decision concerns sequencing the operations on the machines to optimize a given performance indicator (Pezzella, Morganti, & Ciaschetti, 2008). In a job shop, each machine can be utilized more than once to complete a job. To further illustrate, Figure 1.5 shows a job shop system consisting of four machines. Two components of *A* and *B* must be processed, and each component has its own route to process.

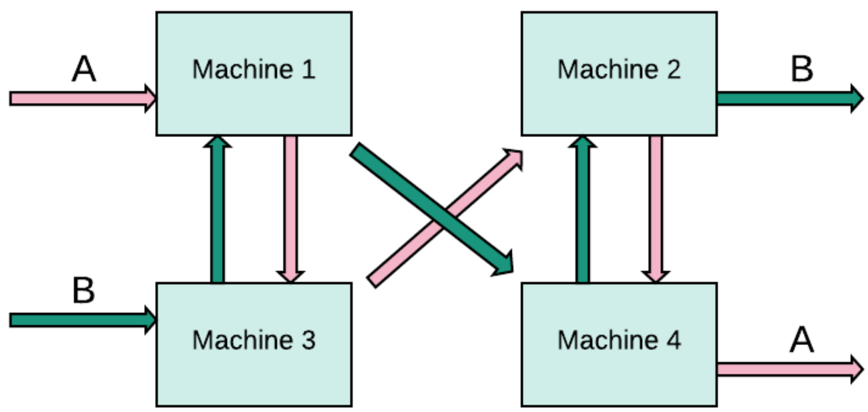

Figure 1.5 A typical job shop (Y. Liu, Dong, Lohse, Petrovic, & Gindy, 2014)

JSP has proven as an NP-hard problem (Garey, Johnson, & Sethi, 1976). For solving realistic cases with more than two jobs, many solution algorithms have been proposed. There are two types of algorithm classifications: hierarchical approaches and integrated approaches. The hierarchical approaches independently allocate and sequence operations on machines, whereas in integrated approaches, these two sub-problems process jointly.

1.1.5 Flexible job shop

The job shop scheduling problem (JSP) is one of the most common scheduling problems due to the wide applicability for manufacturing systems. In a modern manufacturing setting, to achieve flexibility and reliability and to increase performance, typically, several machines are eligible to perform similar tasks. Taking this into account, a FJSP generalizes the classical job shop problem where an operation can be carried out on a set of alternative machines. Thus, FJSP flexibility enhances the complexity of the problem since it demands an additional level of decisions. In FJSPs, there are two distinct sub-problems: assigning operations to the machines and sequencing the assigned operations on each machine. Hence, FJSPs are non-deterministic polynomial-time (NP-hard), most of which cannot be solved by exact techniques. Generally, flexibility in job shop refers to machine flexibility, and it is more practical in real-world applications. In a manufacturing setting, the two types of FJSP includes: Total FJSP (T-FJSP) and Partial FJSP (P-FJSP). As for T-FJSP, every machine can be chosen to process different operations, while for the P-FJSP, processing operations are restricted to only eligible machines (Kacem, Hammadi, & Borne, 2002).

Regarding the FJSP addressed in this thesis, there are some main assumptions and structural constraints of machine scheduling in this environment. These are summarized as follows:

- Jobs are independent and there are no priorities among them.
- Among operations of various jobs, no precedence constraints occur; nevertheless, each job has its own predetermined sequence of operations.
- Each machine can process at most one operation at a time.
- All jobs and machines are available at time zero.
- Processing time is deterministic and it includes setup time.

1.2 Energy-efficient scheduling

Industrial sectors are facing growing pressure to reduce their carbon footprint that is driven by concerns associated with the rising cost of energy, energy security, and environmental impacts. Statistics reveal that manufacturing companies consume almost a third of global energy consumption and generate 36% CO_2 of the world (Indicators, 2007). For example, as shown in Figure 1.6, this trend of energy consumption grows considerably by 2040, in China (Yin, Li, Gao, Lu, & Zhang, 2017). Lowering the energy usage is the most significant step in this process, while still keeping the efficiency and quality of production systems high. Although investment in replacing old machinery can help with energy-saving (Mori, Fujishima, Inamasu, & Oda, 2011), the perspective of energy-efficient scheduling with no or little investment should not be overlooked. Incorporating the concept of energy consumption as one of the decision-making criteria in shop floor scheduling is quite new (Mansouri, Aktas, & Besikci, 2016).

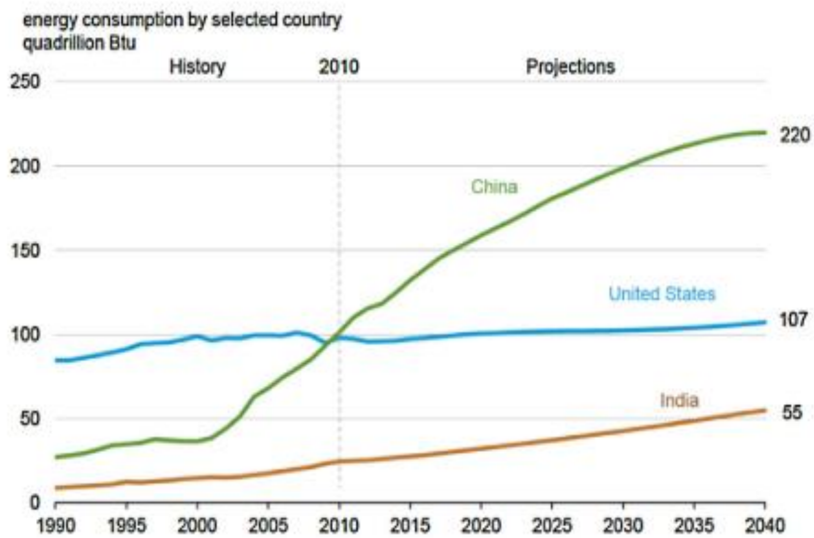

Figure 1.6 Energy consumption in different countries of China, USA, and India (Yin et al., 2017)

Indeed, incorporating energy efficiency in industry is potentially the most cost-effective method of tackling energy security, environmental and economic challenges (International Energy Agency, 2017). Energy efficiency is defined as having the same output with less energy consumption (Patterson, 1996). With the aim of achieving sustainable manufacturing in scheduling, implementing energy efficiency policies controls the energy consumption in the shop floor. In the production scheduling area, FJSP is considered as one of the energy-intensive configurations among all the industrial shop floors. Nevertheless, due to the growing demand for flexibility, FJSP has been considerably adapted in a great number of industrial sectors, including automobile assembly, textile, chemical material processing and semiconductor manufacturing(Lei, Li, & Wang, 2018).

1.3 Integrated production and maintenance planning

In industry, the main aim is to have more reliability and higher availability of the primary source, machines, along with improved production efficiency and high-quality products (Wang & Liu, 2014). To achieve such goals at the operational scheduling level, it is inevitable to schedule maintenance activities in production planning for any failure-prone manufacturing system. In broad terms, scheduling production and maintenance operations separately will yield sub-optimal solutions in an industrial plant (Hadidi et al., 2012). However, the integrated model is expected to provide an optimal solution for a production system with objectives with a conflicting nature (Hadidi et al., 2012). Figure 1.7 portrays the viable interactions between distinct elements of a production system (Hadidi et al., 2012).

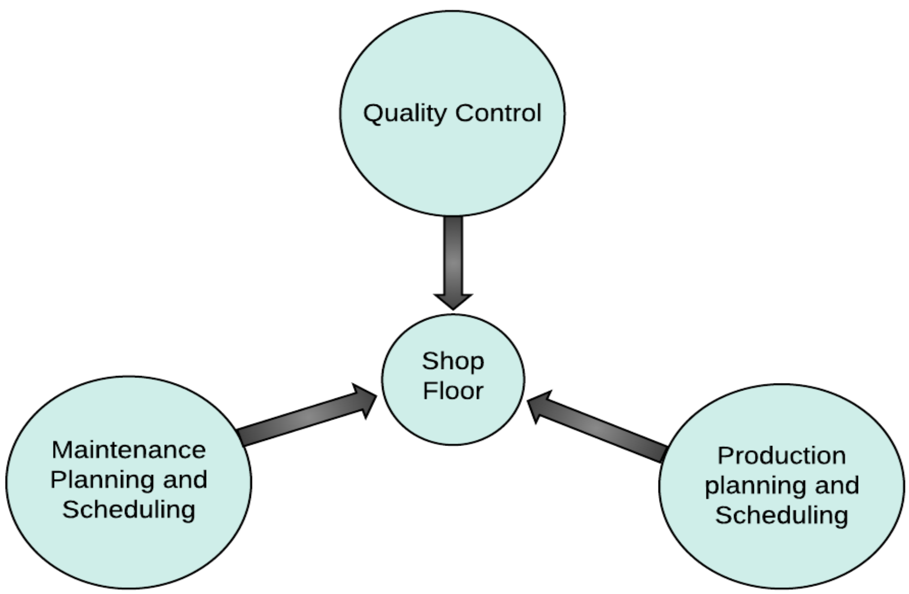

Figure 1.7 Coordination of different elements in a real-life practice

Maintenance is known as actions taken to maintain machines in good operation which is required for a smooth production system (E. Pan, Liao, & Xi, 2010). Since machine breakdowns and scheduled maintenances make machines unavailable, three types of unavailability constraints can be mentioned:

1. Unavailability periods are fixed (deterministic) where the maintenance period and its duration are determined in advanced.
2. Unavailability constraints are decision variables (flexible) where maintenance period and/or its duration are determined with production scheduling together.
3. Unavailability periods have a stochastic nature because of machine breakdown. In this instance, the time that the machine can fail is subjected to a certain distribution, where the failure rate of the machine can be either constant (e.g. exponential distribution) or increasing (e.g. Weibull distribution) (Wang, 2013). Obviously, as a machine continues to operate, the failure rate will increase due to deterioration from usage (Lu, Cui, & Han, 2015).

The two main types of maintenance tasks can be categorized as:

- Corrective maintenance (CM): It is unscheduled maintenance and carries out after systems failure to restore the system to an operational state (Pargar, Kauppila, & Kujala, 2017). This type of maintenance can be referred to as a run-to-failure or reactive strategy (Rahmati, Ahmadi, & Govindan, 2018).
- Preventive maintenance (PM): It is intended to reduce the probability of failure and it is conducted before systems failure (Nwadinobi & Ezeaku, 2018).

More precisely, the objectives of the PM can be summarized as follows:

- To decrease the possibility of failures in the machines and to enhance their reliability during processing;
- To enhance the operational life of the equipment (asset management);
- To make improvement in production planning and its management;
- To increase the operators’ safety (Ruiz, Carlos García-Díaz, & Maroto, 2007).

Besides, Weinstein and Chung (1999) have differentiated two different strategies for PM as mentioned below:

- Interval-based PM: This technique is derived from the periodic version of the PM where the maintenance actions are performed in a predetermined interval (Rahmati et al., 2018).
- Run-based PM: In this version of PM, decisions are made according to the cumulative run time of the production system.

Regarding the unavailability period of the machine and the possibility of interruption during a processing operation, it should be noted that there are three types of settings as listed below:

- Resumable case: Once maintenance activity is done, processing can resume from the point that had been stopped.
- Semi-resumable case: An additional set-up time is required when operation processing is resumed.
- Non-resumable case: After maintenance activity has been done on a machine, the interrupted operation needs to be fully reprocessed (M. Zandieh, Khatami, & Rahmati, 2017).

1.4 Research motivation

Energy consumption and carbon emissions are two major issues for manufacturing sector to operate in a green condition. One cost-effective strategy for lowering carbon footprints in a manufacturing procedure is to develop scheduling that involves sustainability aspects. Accordingly, efficient scheduling has a great effect on a system performance and the concept of green scheduling. Additionally, the integration of PM planning in production planning is required to maintain machines in a good operational state. It is believed that in the absence of PM, machine deteriorates quickly which lead to unexpected breakdowns of machine and production operations leading to extreme unexpected downtime. With a well-planned production and maintenance planning, producers can timely satisfy customer’s demands along with the high product quality.

This research focuses on developing an integrated plan for maintenance and production. The scheduling problem is in a flexible job shop industrial environment in which both traditional and energy-efficient aspects are modeled. The modeling approach has been established based on age-based PM which is still a dominant maintenance policy in industrial plants since it is easy to implement. Moreover, it is assumed that machines may break down, and as a result machines will be unavailable for processing operations. According to the author, the present work is the first study developing flexible PM activities in a flexible job shop with the stochastic nature of machines' failure while processing operations. Another point can be distinguished: since the maintenance tasks interrelate to the availability of the repairmen and their hiring cost, this constraint is additionally modeled; as a result, the concept of opportunistic maintenance is introduced in our problem.

1.5 Research gap and contributions

Flexible job shop scheduling is the most common scheduling model in a real manufacturing system; as a result, we consider this shop floor environment in this thesis. Even though there are many studies on production-maintenance scheduling problems, there is hardly any research available on integrating FJSP with PMs.

Additionally, industrial requirements have developed from the common conventional performance criteria, such as cost and system reliability, towards the new trends in terms of sustainability and integrating practical constraints in scheduling models, which is seldom considered in the studies. So, in this research, the focus is on an energy-aware FJSP incorporating the availability of the maintenance team in performing maintenance tasks.

It should be noted that most of the joint production and maintenance operations are considered deterministic modeling for solving the problem. However, due to uncertain events occurring in the production system, scheduling problems are stochastic and dynamic in nature. Indeed, deterministic scheduling is not applicable for uncertain environments (He, Sun, & Liao, 2013). In the current work, an approach was developed based on consideration of machine breakdowns leading to the temporary unavailability of a machine.

The salient contributions of this thesis can be summarized as follows:

- Energy consumption in the workshop is formulated in modeling with regard to different states of the machines, i.e. idle and operation;

- Incorporating a novel PM scheme in scheduling to optimize the overall production performance and availability. In PM planning, the optimal age-based maintenance policy is incorporated.

- Developing the stochastic FJSP considering the uncertainty related to the breakdown of the machines.

- In this study, maintenance crew constraint is considered in the mathematical formulation and simulation together with the conventional constraints existing in the flexible job shop context.

1.6 Thesis outline

This thesis discusses a wide range of content about energy-aware scheduling and maintenance activities. The study comprises a comprehensive literature review as well as the trend of research around energy-efficient production scheduling and maintenance planning. Following the literature review, descriptions of a mathematical model, simulation, and proposed algorithms will be explained in full detail in the upcoming chapters. The structure of this thesis is as follows:

Chapter 1 presents a brief explanation of the underlying aspects of the work.

Chapter 2 includes the publish papers pertinent to this work which are mainly classified into two categories: (1) energy-efficient scheduling, and (2) integrated production-maintenance planning.

Chapter 3 describes the problem and the proposed mathematical model thoroughly.

In Chapter 4, the maintenance simulation and meta-heuristic algorithms implemented for the research problem are explained in detail. Then, the computational results and the outputs of the algorithms are presented.

Finally, in Chapter 5, a summary of this research and future research opportunities are provided.

2. LITERATURE REVIEW

2.1 Production scheduling

FJSP has significant practical relevance in quite a few industries (Lei, Zheng, & Guo, 2017). Researchers have employed various objective functions, assumptions, and solution techniques since the pioneering works of Brucker and Schlie in 1990, where they proposed a scheduling problem with two jobs and makespan as an objective. As a whole, exact methods and approximation methods can solve FJSP. Exact methods comprise branch and bound algorithm, mixed integer programing, and lagrangian relaxation method (Meng, Zhang, Shao, & Ren, 2019). However, due to the complexity of the FJSP, approximate methods have been extensively applied to obtain a feasible schedule to optimize the predefined objective function. The approximation method is composed of heuristic algorithms and various meta-heuristic algorithms, where meta-heuristic algorithms are more efficient compared to the previous ones to solve scheduling problems (X. Li & Gao, 2016). Genetic algorithm (GA), simulated annealing (SA), tabu search (TS), and artificial bee colony (ABC) are included in the meta-heuristic algorithms.

Focusing on MILP modeling of scheduling problems, there are two main ideas. One of them was proposed by Wagner in 1958, based on the sequence-position variable. Variables in this kind of modeling are defined according to the notation that each machine has a fixed number of positions to assign the operations. The second is introduced by Manne (1959) whose idea relies on precedence variable approach. Variable denotes the sequence of operations which are allocated to the same machine. Looking at the literature, Blazewicz et al (1991) is the first study that addresses mathematical models for scheduling problems. They established mathematical programming formulations for single-machine, parallel-machine and job shop scheduling problems. Although mathematical programming formulation is inefficient in solving the problem in large size, it provides the key step of understanding the structure of scheduling problems (Demir & Kürşat Işleyen, 2013). Later, Choi and Choi (2002) presented a mixed integer linear programming (MILP) model to deal with the FJSP with regards to sequence-dependent setup times.

Imanipour and Zegordi (2006) dealt with minimizing Total Weighted Earliness/Tardiness (TWET) of jobs in the FJSP. The problem was modeled as an MINLP, and an algorithm based on a Tabu Search (TS) was designed to solve large-scale problems. Fattahi et al. (2007) presented the first position-based MILP, based on Wagner's modeling idea, for FJSP; and, they also developed six different hybrid searching structures. Numerical experiments were applied to assess the performance of the established algorithms. Demir and Kürşat Işleyen (2013) examined the three previously developed MILP models, which relied on sequence-position variable, precedence variable, and time-indexed variable; then, based on the models, five different mathematical formulations were established for FJSP with the objective function of minimizing makespan. Models were considered with different sized test problems. According to the acquired results, they recommended using the model based on the precedence variable. Roshanaei et al. (2013) proposed two new position- and sequence-based MILP models for the FJSP that more efficiently can be used to solve partially and totally F-JSSPs. A hybrid of Artificial Immune and Simulated Annealing (AISA) Algorithms was applied to deal with larger instances of the FJSP.

2.2 Energy efficient production scheduling

Numerous models and solution techniques have been developed for traditional scheduling problems; nevertheless, research on energy-efficient scheduling, low-carbon scheduling, and sustainable scheduling in the workshop is quite new (Meng et al., 2019). The work of Mouzon et al. (2007) is one of the earliest attempts done to reduce energy consumption with the help of production scheduling. They developed operational methods to minimize the energy usage of manufacturing equipment. It was found that non-bottleneck machines consumed a significant amount of energy when kept idle in comparison to other machines in the system. A turn-on and turn-off scheduling framework were proposed to control overall energy consumption in machines. According to statistics, approximately 80% of the energy of machines is utilized when they remain in idle mode. Later, Yildirim & Mouzon (2008) proposed the usage of this framework for single machine scheduling that optimizes total energy consumption and total tardiness.

Shrouf et al. (2014) developed a model to reduce energy consumption costs for single machine production scheduling while factoring variable energy prices during a day. They considered the continual changes in energy costs as a major element in the scheduling problem at the machine level. To solve the problem, three machine states were identified: processing, idle, and shut down, and a GA was applied to obtain near-optimal solutions. Next, the outcomes of the proposed model were: 1) to determine when to start processing every job, 2) to determine when the machine should be idle or shut down and, 3) to come up with the exact costs of energy consumption for the machine.

To achieve an energy-aware single-machine scheduling, Rubaiee and Bayram (2019) formulated a mixed-integer multi-objective to minimize the total completion time and total energy cost under time-of-use (TOU) electricity taxes, where preemptions were allowed. To solve larger-sized problems, they developed two ant colony optimization (ACO) algorithms, based on Swarm Intelligence methods, to obtain an approximate Pareto front.

For certain production systems, it is impossible to switch off machines during idle periods. The reason can be either restarting the machines call for a great deal of additional energy or frequent switching may cause damage to the machine (R. Zhang & Chiong, 2016). Another useful technique to reduce energy usage by processing machines is speed scaling. In this mechanism, the processing speed of machines can vary, resulting in different processing times and, more importantly, different energy consumption rates (Che, Wu, Peng, & Yan, 2017). Clearly, when a machine is working at a higher speed, the processing time reduces but at the same time energy consumption rises. Speed-scaling problems have been investigated by many researchers. For example, Fang et al.'model in 2011 considered peak power load, energy consumption, and associated carbon footprint to optimize a two-machine flow shop (FS) scheduling problem. In the proposed model, the operation speed was considered as an independent variable, which can affect energy consumption. Wierman et al. (2012) presented a detailed review of the model related to speed-scaling problems.

Also, Fang et al. (2013) further examined the impacts of constrained peak power usage on a FS scheduling problem. In particular, they proposed two mixed integer programming formulations based on the work of Manne (1960) and Wagner (1958). Dai et al. (2013)

applied the on/off strategy to a flexible FS scheduling problem with the objectives of the minimization of makespan and energy consumption in manufacturing systems. Luo et al. (2013) addressed the problem of hybrid flow shop (HFS) scheduling concerning both production and avoiding peak times in scheduling. In order to solve this problem, a new ant colony optimization algorithm has been developed to optimize both makespan and electric power costs with the presence of variable energy prices.

Liu et al. (2013) developed a branch and bound method to minimize the energy consumption during idle time in the permutation flow shop (PFS) scheduling problem. Two lower bounds were proposed, then an improved NEH heuristic algorithm was applied to the initial upper bound. To validate the efficiency of the proposed model, it was compared with the makespan minimization criterion in the PFS environment. Based on the results, they deduced that their model provided more energy-saving solutions. Considering the dynamic nature of scheduling problems such as new job arrivals and machine breakdowns, Tang et al. (2015) used an improved PSO to deal with the multi-objective problem, including the makespan and energy consumption, for a flexible FS scheduling. Additionally, in another study presented by Lin et al. (2015), FS scheduling was explored. The objective of this study was to minimize the makespan and carbon footprint, which was accomplished through a multi-objective teaching-learning-based optimization (TLBO) algorithm. Ding et al. (2016) investigated a PFS scheduling problem in order to minimize both the total carbon emissions and the makespan. They designed two new multi-objective optimization algorithms to solve the problem.

Mansouri et al. (2016) formulated a mixed integer linear multi-objective optimization model for a two-machine PFS where machines have variable speeds. They considered minimizing makespan and total energy consumption as objectives and used a novel heuristic to cope with combinatorial complexity in medium- and large-sized problem instances. In another recent work, Lei et al. (2018) studied the bi-objective energy-efficient HFS scheduling problem. In fact, this problem encompassed three sub-problems, namely, scheduling, machine assignment, and speed selection. In order to minimize total energy consumption and total tardiness, a new teachers' teaching-learning-based optimization (TTLBO) was adapted.

Li et al. (2018) studied the hybrid flow shop (HFS) scheduling problem with two objectives, minimization of the makespan as well as energy consumptions. They devised a multi-objective optimization algorithm to solve this bi-objective problem in regard to the setup energy consumptions. Li et al. (2019) applied a two-level imperialist competitive algorithm (TICA) for energy-efficient hybrid flow shop scheduling problem (EHFSP). EHFSP includes three objectives of total tardiness, makespan, and total energy consumption. They considered these objectives with relative importance in which the latter objective had the least importance.

From the job shop scheduling perspective, Lei and Guo (2015) presented a dynamical neighborhood search (DNS) for the dual-resource constrained (DRC) job shop. A lexicographical method was applied with the aim of minimizing carbon footprint and makespan. Selmair et al. (2014) formulated a linear optimization model with the objective of minimizing the total energy costs in a job shop (JS) production system. Afterward, May et al. (2015) studied the production scheduling problem in a JS system aimed towards minimizing energy consumption and makespan. They modeled energy-efficient JS based on different operational states of a machine, that is, off, standby, idle, set-up, and working. They focused on developing different policies related to the duration of each state and power requirements of different states. A green genetic algorithm was designed to find Pareto front solutions. Zhang and Chiong (2016) investigated a JS scheduling problem with the total weighted tardiness (TWT) in addition to the total energy consumption (TEC). They used a multi-objective GA to solve this bi-objective optimization problem. Recently, Masmoudi et al (2019) studied a JS scheduling problem with respect to energy aspects. The objective was to find a schedule that minimized the energy cost with the variable electricity cost profile. Two integer programming models, namely, a time-indexed formulation and a disjunctive one were proposed to cope with the addressed problem.

It is noted that relatively few researchers discuss the reduction of energy consumption in a FJSS problem. Regarding an energy-efficient model, Jiang et al. (2014) developed a multi-objective FJSS problem with the objectives of the minimization of the makespan, processing cost, energy consumption, and cost-weighted processing quality. The authors proposed a non-dominated sorting GA to resolve the multi-objective optimization problem.

Yin et al. (2017) studied a FJSS where optimization of productivity, energy efficiency and noise reduction were considered in a multi-objective low-carbon mathematical scheduling model.

Jiang and Deng (2018) recently established a mathematical model and bi-population based discrete car swarm algorithm (BDCSO) for a FJSS problem to minimize the total energy consumption cost and the earliness/tardiness cost. In Lei et al., (2017), a shuffled frog-leaping algorithm (SFLA) was applied to minimize the workload balance and total energy consumption in a FJSP. Another energy-efficient oriented FJSP was addressed by Lei et al., (2018), in which they elaborated on the energy consumption threshold. They proposed a model for the bi-objective problem, which minimized makespan and total tardiness provided that the total energy consumption did not exceed a given threshold. They applied a two-phase meta-heuristic (TPM) to solve the model. Piroozfard et al. (2018) designed an energy-efficient FJSP with the objectives of minimizing the total carbon footprint and the total late work. In their model, two states of the busy and idle for machines were formulated in the scheduling period. In order to solve the presented problem effectively, an improved bi-objective genetic algorithm (MOGA) was used to obtain high-quality non-dominated scheduling.

2.3 Integrated production scheduling and maintenance planning

In industrial settings, firm interactions between production and maintenance operations can be witnessed in the shop floor. The joint scheduling of production and maintenance operations should be considered to balance the consumption and availability of the resource (Wang & Liu, 2014). Maintenance activity occupies production time and frequent maintenance causes delay production; consequently, well-planned maintenance activities are required according to jobs' processing time and the status of the machines (E. Pan et al., 2010). The joint scheduling of production-maintenance operations is referred to as "availability constraints" in production systems. Roughly, they are classified into two different research directions (Gao, Gen, & Sun, 2006):

(i) Fixed unavailability constraints: The unavailability period is known and fixed in advance for the maintenance tasks.

(ii) Non-fixed unavailability constraints: The unavailability period is supposed to be flexible and is scheduled during the production procedure by decision-makers.

During recent years, this type of schedule has been an interesting topic to many researchers and practitioners in different shop floors (e.g. a single-machine scheduling problem, parallel machine scheduling problem, flow shop scheduling problem, and job shop scheduling problem, etc.). Thus, different assumptions and approaches have been made to deal with this integrated optimization model since the beginning of the 1990s. Sanlaville and Schmidt (1998), Schimdt (2000), and Ma et al. (2010) provided comprehensive reviews about scheduling problems with limited machine availability.

2.3.1 Integrated production-maintenance scheduling for a single-machine

Joint production scheduling and maintenance planning comprise a vast area of models. The single machine area is self-explanatory which is a simple version of these models. The following is a brief review of the single-machine scheduling problems and maintenance operations. Adiri et al. (1989) considered the problem of scheduling tasks on a single machine to minimize the total completion time. The machine may break down during the operation. They proved that the Shortest Processing Time (SPT) policy minimizes the objective in the case where the machine is subject to a single breakdown. The authors showed that for the case of multiple breakdowns, SPT minimizes the expected total completion time when the times to breakdown were exponentially distributed. Liao and Chen (2003) studied a single-machine scheduling problem to minimize the maximum tardiness with periodic maintenance and non-resumable jobs. They developed a heuristic along with a branch-and-bound algorithm to solve this problem.

Cassady and Kutanoglu (2005) integrated an age-based PM planning in a single machine scheduling in a way that the total expected weighted completion time of jobs was minimized. For this problem, they compared the acquired result of the integrated solution and implemented each approach separately. Their analysis indicated that integrating the two decision-making processes showed better results. Their study was followed by Sortrakul et al. (2005), in which they developed three GAs to optimize a joint model for production and

PM planning. Based on the evaluation of various instances from different sizes, they showed that their GA-based algorithms were efficient for optimizing the integrated problem.

Sadfi and Formanowicz (2005) proposed an algorithm called MSPT heuristic stemmed from the SPT algorithm for a single machine scheduling subject to a single period of maintenance. The total completion scheduling problem was used to decide the optimal solution. The computational experiments indicated that the MSPT heuristic improved the result of the SPT heuristic. Sbihi and Varnier (2008) elaborated on a single-machine scheduling problem with several maintenance periods to minimize the maximum tardiness. They distinguished two cases of unavailability period. In the first scenario, maintenance was required after a periodic time interval. In the second scenario, they dealt with the flexible periodic version in which the maximum continuous working time allowed of the machine was determined. An efficient heuristic and branch-and-bound algorithm were proposed and tested computationally.

Chen (2008) dealt with flexible and periodic maintenance in a single-machine scheduling problem where the objective was to minimize the makespan. They proposed two mixed binary integer programming (BIP) models for drawing the optimal solution. A heuristic, based on the longest processing time first (LPT) rule, was applied for finding the near-optimal solution for large-sized problems. In the interim, the maintenance scheme was termed flexible maintenance since they supposed that the machine must be stopped periodically for maintenance during predefined $[u, v]$ period, in which jobs were non-resumable.

Chen (2009) investigated a single-machine scheduling problem with periodic maintenance in order to find a schedule that minimizes the number of tardy jobs. In their study, a schedule included several maintenance intervals and jobs were non-resumable. A branch-and-bound algorithm was proposed to optimize the schedule. Based on Moore’s algorithm, a heuristic was also developed to provide a near-optimal schedule for the problem. Low et al. (2010) addressed the problem of scheduling jobs with the aim of minimizing the makespan and availability constraints, which resulted from periodic maintenance activities.

In Low's work, a single-machine problem was considered with two maintenance schemes simultaneously:

- After a specified interval, a machine should stop for maintenance tasks
- After a fixed amount of jobs processed, tools should change

They proposed six types of heuristic algorithms and compared the performances of them. For a single-machine problem with the aim of minimization of the number of tardy jobs, Lee and Kim (2012) suggested a mixed integer program and a two-phase heuristic algorithm. Periodic maintenance activities were planned with fixed time intervals, but preemption of the jobs (for the maintenance activities) was not permitted. In their algorithm, an initial solution was obtained in the first phase, according to a method modified from Moore's algorithm, then they obtained the optimal.

Detienne (2014) studied a single-machine scheduling problem which was subject to deterministic machine availability constraints. He investigated three cases of resumable, non-resumable, and semi-resumable jobs. The objective was to minimize the weighted number of late jobs and the problems solved efficiently through the use of a MILP approach. The author supposed that unavailable intervals were fixed in advance. Cui and Lu (2017) furthered their work by considering non-fixed periodic PMs for resumable and non-resumable cases. They proposed a heuristic, based on Earliest Release Date-Longest Processing Time (ERD-LPT) and a branch and bound (B and B) algorithm, as two complementary algorithms, to search the optimal schedule for different sized problems. Additionally, Zhang et al. (2017) addressed a single-machine scheduling problem and the aim was to minimize both the makespan and the total completion time. They examined two scenarios where the number of maintenance activities is fixed and non-fixed. Two polynomial-time algorithms were developed to achieve the best solution for this problem.

2.3.2 Integrated production-maintenance scheduling problem for parallel machines

Lee and Chen (1999) studied the parallel-machine scheduling problem for a set of jobs such that the total weighted completion time of jobs was minimized. In the defined problem, each machine is given one maintenance routine during the planning period with respect to two different scenarios:

- Sufficient resources were available so that machines could be maintained simultaneously.
- Only one machine could be maintained at a given time.

For solving both cases to optimality, they proposed a branch and bound exact solution algorithm, based on the column generation approach. It was noted that their proposed algorithm was capable of solving medium size problems within a reasonable computational time.

Liao et al. (2005) focused on a problem of two-parallel machines in which one machine was not available during a time period due to either preventive maintenance or periodical repair. This unavailability period was fixed and known in advance. The objective was to minimize the makespan for both non-resumable and resumable cases. For solving these problems, they adapted an algorithm based on the TMO algorithm. Extending their work, Lin and Liao (2007) addressed the same problem for the case in which there were two unavailable periods. These two unavailable periods with the same length were fixed and known in advance.

Liao and Sheen (2008) integrated availability and eligibility constraints within the problem of processing n jobs on m identical parallel machines. They considered the minimization of the maximum makespan as an objective. In their addressed problem, the availability and eligibility constraints were defined as follows:

- The machine availability constraint meant that a number of identical machines were not always available for operations.
- The machine eligibility constraint denoted that certain jobs can only be processed on specific machines.

In order to formulate this scheduling problem into a set of maximum flow problems, they applied a network flow approach. Xu et al. (2008) studied a parallel machine scheduling problem with a periodic maintenance scheme to optimize the makespan. Two heuristics algorithms, BFD (Best Fit Decreasing) algorithm and LPT (Largest Processing Time first) algorithm, were applied to address the problem. Berrichi et al. (2009) considered a bi-objective approach in the parallel machine that joined production and maintenance scheduling problem. The purpose was to optimize two criteria at the same time which were the makespan and the unavailability of the system. Thus, two types of decisions were taken at the same time:

- Finding the best assignment of n independent jobs on m machines
- Deciding when to perform the PMs for each machine, while the number of maintenance actions and the maintenance time frames were not determined beforehand.

As a solution method, they implemented a genetic algorithm. Besides, Mellouli et al. (2009) investigated PM planning in the identical parallel machine scheduling problem so that the summation of completion times ($\sum_{i=1}^{n} C_i$, where n indicated the number of jobs) minimized. The authors proposed three exact methods to solve the problem: that is, mixed integer linear programming methods, a dynamic programming-based method, and a branch-and-bound method.

Sun and Li (2010) coped with the scheduling problem relating to a set of n jobs on two identical parallel machines with the aim of minimizing the makespan. For maintenance planning scheme, they assumed that the time between two consecutive maintenance operations cannot exceed an upper limit T. In their study, they considered two scheduling models:

(1) The maintenance operations carried out periodically, dealt with a heuristic algorithm named MH_{FFD}.
(2) A fixed maintenance operation carried out jointly during production scheduling where the classical SPT algorithm was applied to solve it.

Lee and Kim (2015) developed a branch and bound algorithm for a problem in which a PM was required for each machine after processing a given number of jobs. The problem of scheduling jobs was assumed to be performed on two identical parallel machines with the objective of minimizing total tardiness. Shen and Zhu (2018) studied a parallel-machine scheduling problem with periodic PM with the aim of minimizing the makespan. They assumed that processing and maintenance time were uncertain variables. To address this problem, an improved LPT rule was suggested, and they showed its effectiveness compared to the LPT.

2.3.3 Integrated production-maintenance scheduling problem for flow shop problem

The two machines flow shop (FS) scheduling without maintenance constraints with the aim of minimization of the makespan can be viewed as the first 'multi-machine' scenario in the field of scheduling problems (H Allaoui & Artiba, 2004). In the studied problem, Johnson's algorithm can be used to schedule the jobs optimally in the shop. Afterward, the presence of PM intervals in machine availability has been explored by several researchers. Lee (1999) addressed the two-machine FS problem with fixed availability constraints. They considered the problem in two cases: resumable and non-resumable. They developed dynamic programming algorithms and heuristic methods for solving the problem.

Aggoune (2004) investigated non-preemptive FS scheduling with availability constraints. Two cases when the starting time of maintenance tasks was fixed or non-fixed were studied. The author proposed a GA and a TS to approximately solve the makespan minimization problem. Allaoui and Artiba (2004) studied a HFS scheduling problem under maintenance constraints to minimize flow time and due date. Setup, cleaning, and transportation times were also considered. They used the SA algorithm to solve the problem. Further, three heuristic algorithms, namely, LPT, SPT, and EDD were applied to generate better initial solutions.

- SPT rule: Prioritizing jobs based on the shortest processing time.
- LPT rule: Prioritizing jobs with the longest processing times, first.
- EDD rule: Prioritizing jobs according to the earliest due dates.

Allaoui and Artiba (2006) dealt with the two-stage HFS scheduling problem where a single machine on the first stage and multiple machines on the second stage to minimize the maximum completion time. They assumed that each machine was subject to at most one unavailability period. Also, the start time and the end time of each period were determined beforehand and the case of non-resumable was considered. They presented a Branch and Bound algorithm for this problem.

Ruiz et al. (2007) integrated PM operations in a PFS problem which was intended to minimize the makespan. Six heuristic and metaheuristic methods were applied to a number of instances and the outputs were compared. Then, based on the results they concluded that modern Ant Colony and GA provided very efficient solutions for this problem. Safari et al. (2010) explored a FS scheduling problem under condition-based maintenance (CBM) constraints to minimize the expected makespan. Additionally, they focused on non-resumability, where the job needed to restart after interruptions. In solving the proposed problem, they mentioned two barriers:

- The stochastic feature of machine failure which was tacked by simulation
- The NP-hardness of scheduling problems was done by metaheuristic algorithm

They developed a hybrid meta-heuristic algorithm based on a SA and a TS to find the near-optimal solution. Further, Safari and Sadjadi (2011) addressed FS configuration under the assumption of machine degradation to minimize expected makespan. They considered condition-based maintenance (CBM) strategy for the non-resumable case. Under these considerations, they developed a hybrid algorithm based on GA and SA.

Zandieh et al. (2017) optimized joint production and PM scheduling problem in a bi-objective HFS problem with sequence-dependent setup times. The objective functions were the minimization of the makespan and unavailability of the system. Simultaneously, two decisions were required for consideration:

- To find the optimal allocations of jobs and sequencing them on machines to minimize the makespan
- To decide how often to carry out PM activities to minimize the system unavailability

A non-dominated sorting genetic algorithm-II (NSGA-II) and a hybridized NSGA-II (HNSGA-II) were developed for the research problem.

2.3.4 Integrated production-maintenance scheduling problem for job-shop scheduling

The job shop scheduling problem (JSP) with availability constraints has been investigated from multiple angles. Two mathematical models were presented by Azem et al. (2007) to deal with non-preemption JSP with non-fixed unavailability periods with the objective of minimizing makespan. The first one was based on the disjunctive graph while the second one was the time-indexed model. The test results revealed that disjunctive formulation provided better results than the time-indexed one. In Zribi et al. (2008), a hierarchical approach was presented to resolve a JSP with availability constraints. A heuristic was used to assign operations on machines, and then a GA was applied to sequence operations on machines to minimize the makespan.

The JSP with sequence-dependent setup times and PM were investigated by Naderi et al. (2009). The minimization of makespan was considered as an optimization criterion. A SA and a GA were applied to address this problem. Mati (2010) studied the makespan minimization in a JSP with availability constraints. To solve the problem, the disjunctive graph model and a taboo thresholding heuristic were used.

Ben Ali et al. (2011) studied JSP under periodic unavailability periods for PM tasks. The goal of scheduling was to minimize the makespan and the total maintenance cost. Two types of performing PM were considered. In the first type, they supposed that machines must be maintained regularly after a fixed interval of time ($T, 2T, \ldots$). The second type of PM was carried out after each T process time. To solve this problem, they presented a multi-objective genetic algorithm (MOGA).

Azem et al. (2012) developed heuristics to minimize makespan for the JSSP where processing operations were subject to interruption due to resource unavailability periods and unavailability periods were non-fixed. Sarker et al. (2013) presented a Hybrid Evolutionary Algorithm to optimize makespan for solving JSPs along with machine maintenance. For the breakdown case, a revised schedule was produced by the right shifting method, and the affected operations were impacted from the time of breakdown on the broken machine.

Fnaiech et al. (2015) proposed a new heuristic method to address a JSP where machines were subject to fixed PM planning. They combined a Modified Genetic Algorithm (MGA) and Heuristic Displacement of Genes (HDG) to solve the considered problem to minimize c_{max}. Benttaleb et al. (2016) tackled non-preemptive two-machine JSP when they considered unavailability constraints on one machine. They developed a branch and bound (B&B) algorithm in order to minimize makespan.

Benttaleb et al. (2018) presented two mixed integer linear programming models regarding non-preemptive JSP under availability constraints in order to minimize makespan. They assumed that unavailability periods were known in advance. Jackson’s algorithm does not guarantee the optimality; consequently, the authors represented some properties concerning the optimality of this algorithm under availability constraints. They then proposed a branch and bound algorithm (B&B) based on the proposed rules.

2.3.5 Integrated production-maintenance scheduling problem for flexible job shop scheduling

In the scheduling area, research focusing on the FJSP with availability constraints is the least investigated compared to other scheduling problems. Reviewing the literature, Zribi and Borne (2005) considered a deterministic FJSP model where the unavailability of the machines due to maintenance tasks was determined beforehand. They assumed that preemption of operations was not allowed and the optimization criterion was the minimization of the makespan. Gao et al., (2006) applied a hybrid GA to solve a FJSP with PM activities. In their model, the availability constraints were non-fixed, and thus, the completion time of the maintenance should be determined during the scheduling procedure. Their aim was to minimize three criteria including: makespan, maximal machine workload, the total workload of the machines.

Wang and Yu (2010) developed a FJSP regarding both scenarios of fixed and non-fixed machine availability constraints. Besides, two approaches were considered in their model, single or multiple maintenance planning. Moradi et al. (2011) dealt with an integrated FJSP with PM activities. In the proposed model, they focused on two conflict objectives: the minimization of the makespan for the production, and the minimization of the system unavailability for maintenance. In their model, it was assumed that PM activities must be carried out at fixed intervals and once the PM was performed, there was no probability of a subsequent equipment breakdown.

Li et al. (2014) suggested multi-objective FJSP with maintenance activities. In their study, they assumed the performance criteria were makespan, the total workload of the machines, and the workload of the critical machines. They presented a novel discrete artificial bee colony (DABC) algorithm to solve the model. Mokhtari and Dadgar (2015) investigated joint FJSP and maintenance with the aim of minimizing the total number of tardy jobs. In their model, it was assumed that the machines' failure rates were time-varying because of the environmental situations and the duration of PM was fixed. They developed a MILP model, and the framework using a simulation-optimization. They proposed a SA optimizer and Monte Carlo (MC) simulator for solving the model.

More recently, Mokhtari and Hasani (2017) proposed an energy-efficient FJSP to optimize the makespan, the total availability of the system, and the total energy cost with regard to an integrated production and maintenance operations. They stated that maintenance operations are assumed among the primary source of energy consumption in manufacturing procedures, so production and maintenance operations impose considerable energy cost to the system. Also, to reduce the unforeseen failure and expend the overall availability of the industrial machines, the suitable level of PMs was selected among an available set of services $(p = 1, \dots, P)$ and planned on pre-known periods. In another work, Ahmadi (2016) implemented a simulation model to deal with a multi-objective problem in a FJSP with random machine failure.

Table 2.1 summarizes the previous relevant research in the scheduling field. According to the conducted literature review, previous research is lacking in terms of practical and industrial applications; in real manufacturing settings, joint scheduling of production and maintenance in addition to a set of realistic assumptions is required.

Table 2.1 Summarized previous relevant studies

Author(s)	Machine scheduling	Model with consideration of			Type of Maintenance		Solution approach
		makespan	Cost	Energy	PM	CM	
(Wang, 2013)	Single machine	–	√	–	√	√	-An integer linear programming model
Yildirim & Nezami (2014)	Single machine	–	√	–	√	√	-A mathematical model
Che et al. (2017)	Single machine	–	–	√	–	–	-A mixed-integer linear programming (MILP) model -A basic ε−constraint method
Berrichi et al. (2009)	Parallel machines	√	–	–	√	–	NSGAII
Wang & Liu (2015)	Parallel machines	√	–	–	–	–	-A multi-objective integrated optimization method -NSGA-II
Pan et al. (2018)	Parallel machines	–	–	√	–	–	-A lexicographical method -Imperialist competitive algorithm (ICA)
Liao et al. (2017)	Parallel machines	√	√	–	√	–	NSGA-II algorithm
Liu et al. (2008)	Hybrid flow shop	–	–	√	–	–	-A mixed-integer nonlinear programming model -An improved GA
Ruiz et al. (2005)	Flow shop	√	–	–	√	–	-Ant Colony Algorithms -GA
Safari & Sadjadi (2011)	Flow shop	√	–	–	√	√	-GA -SA
Safari et al. (2010)	Flow shop	√	–	–	√	√	-TS -SA
Yu & Seif (2016)	Flow shop	–	√	–	√	–	-A mixed-integer linear program -A lower-bound-based genetic algorithm (LBGA)
Seif et al. (2018)	Flow shop	–	√	–	√	–	-A mixed-integer linear program -Fuzzy
Tamssaouet et al. (2018)	Job shop	√	–	–	√	–	-disjunctive graph model -SA -TS
Zhang & Chiong (2016a)	Job shop	–	–	√	–	–	A multi-objective genetic algorithm (MOGA)
Gao et al., (2006)	Flexible job shop	√	–	–	√	–	-GA
Dalfard & Mohammadi (2012)	Flexible job shop	√	–	–	√	–	- A mixed-integer nonlinear programming, -GA -SA
Lei et al., (2018)	Flexible job shop	√	–	–	–	–	-A two-phase meta-heuristic (TPM) based on an imperialist competitive algorithm (ICA) and variable neighborhood search (VNS)

Khoukhi et al. (2017)	Flexible job shop	√	–	–	√	–	-A Mixed Integer Nonlinear Program (MINLP) -A bi-level disjunctive/conjunctive graph -Ant Colony Optimization (ACO) approach
Rahmati et al. (2018)	Flexible job shop	√	–	–	√	√	-Simulation-based optimization (SBO)
Our work	Flexible job shop	√	√	√	√	√	-A mathematical model -GA -SA

3. DESCRIPTION AND THE MODEL

3.1 Problem description and assumptions

In recent years, there has been growing concern in energy efficiency in manufacturing enterprises. Since scheduling problem has a direct impact on energy consumption, developing effective production scheduling is one of the priorities in industries. In practice, production and maintenance operations have been viewed as a major source of energy consumption in the industrial system. We consider the scheduling problem in a flexible job shop scheduling environment. The two types of FJSP include: total FJSP (T-FJSP) and partial FJSP (P-FJSP). In a T-FJSP, each operation can be processed on each machine from a set of available machines (J. Li, Pan, Xie, Jia, & Wang, 2010); while in a P-FJSP, each operation can be operated on a set of eligible machines (H. Liu, Abraham, Choi, & Moon, 2007). In this study, we consider a total flexible job shop scheduling environment, so all machines can process every operation. Concerning the maintenance aspect, preventive maintenance is executed as a strategy to decrease the probability of the potential failure of the system before they happen and as a result, it increases the availability of the production system (Khatami & Zegordi, 2017). In this work, a new approach is proposed to cope with two distinct, yet dependent decisions simultaneously: production scheduling decisions, as well as PM decisions.

The goal of this research is to propose a joint production planning and maintenance scheduling model that considers the availability of the maintenance team. We consider integrated production-maintenance planning where the purpose is to minimize the total cost of hiring repairmen, energy consumption, and tardiness penalties. The main aims are to find the optimal machine assignment and operation sequence, to determine if PM is required to be executed between two consecutive operations, and to specify the optimal number of the maintenance crew to be hired for the shop floor to minimize the expected total cost. In order to incorporate energy consumption in the scheduling, the cost of energy usage associated with different states of the machines, that is, operation and idle, is considered in the objective function.

The problem is formulated as a mathematical model for scheduling. We assume the production machines in this environment may break down which causes the unavailability of the machines for the production. Upon a failure, the machine must be fixed by a repairman. To do this, a repairman must be called from the maintenance depot. Thus, the repairmen hiring cost and their traveling time to the shop floor are considered in our model. For the problem under consideration, we will first find the optimal schedules of operations on machines by a genetic algorithm (GA) and simulated annealing (SA); then, unexpected machines' breakdowns are generated for all loaded machines. Accordingly, we apply the proposed maintenance policy based on the obtained optimal replacement ages of the machines and use them in the simulation for an integrated plan of production schedules and maintenance operations. This integrated scheduling problem considers two maintenance actions at the failure time, either replacement or minimal repair. At the failure time, if the age of the machine exceeds the obtained optimal replacement age, we will decide on replacement; otherwise, minimal repair will be required. Moreover, this study considers opportunistic maintenance, which is performing PM on the machines that require (preventively) replacement in the immediate future, if a repairman is already in the shop floor to perform corrective maintenance of a failed machine. The opportunistic maintenance reduces maintenance cost, namely, calling and hiring of a new repairman.

The problem is formulated according to the following assumptions:

- There are a set of n jobs given to be processed on m machines.
- Each job i encompasses a sequence of n_i consecutive operations, where O_{ik} denotes operation k^{th} of job i, which can be processed through a set of machines.
- Since the performances of the machines are different, their processing times of the same job are different, accordingly.
- All the data related to the processing time, energy consumption of the machines in idle and processing modes are deterministic and known in advance.
- Setup times are included in the processing times.
- Jobs are independent and there is no preference among them.
- Each machine can process only one operation at a time.
- All jobs and the machines are simultaneously available at time zero.

- The duration of performing maintenance activities is fixed for each machine.
- The machines' failure processes follow a non-homogenous Poisson process (NHPP).
- If the minimal repair takes place on a machine, it restores the machine to the operating state just prior to the failure.
- Machines do not age during the downtime.
- Replacement action on a machine makes the machine as good as new.
- The age of the machine is an assessment of cumulated operating time after each replacement.
- Processing an operation has priority over the PM activities.

3.2 Mathematical formulation

FJSP is the most intricate shop floor configuration that makes less constraint on a machine, so it extends the search range for a solution (Rajkumar, Asokan, Anilkumar, & Page, 2011). In the mathematical model, our scheduling objective is to minimize the total cost of the system. For that, our objective is to find a schedule that cuts down the cost of hiring repairmen, the cost of energy consumption, and the cost of penalty as a metric of tardiness of finished jobs. Obviously, the downtimes due to failure of the machines, waiting time for the repairman, and planned PM certainly yield an increase in the expected completion time of a set of jobs. The proposed mathematical formulation is presented as a deterministic model. Furthermore, we apply the addressed constraints as rules to ensure the feasibility of the developed solution in the simulation phase. Indices, variables, and parameters used in the model of the problem under investigation can be described as follows:

Indices and sets:

i: index of jobs $i, i' \in \ I = \{1,2, \dots, n\}$

j: index of machines $j, j' \in \ J = \{1,2, \dots, m\}$

k: index of operations $k \in K = \ \{1,2, \dots, n_i\}$

In our study, the employed parameters as defined as follows:

n Total number of jobs

m Total number of machines

R Total number of repairmen in the manufacturing enterprise

O_{ik} Operation k of job i

p_{ik}^{j} Processing time of operation O_{ik} if it is to be performed on the machine j

n_i Total number of operations of job i

β_j Wiebull shape parameter of machine j

η_j Wiebull scale parameter of machine j

g_i Penalty coefficient of job i

C_M^j Minimal repair cost of machine j

C_{RP}^j Replacement cost of machine j

C_{RM} Cost of hiring each repairman

e_{idle}^j The unit energy cost of machine j in idle condition per unit time

e_{run}^j The unit energy cost of machine j in processing condition per unit time

D_{PR}^j Duration time for each preventive replacement of machine j

D_{MR}^j Duration time for minimal repair at failure of machine j

D_{RP}^j Duration time for failure replacement of machine j

D_i Due date of job i

H It is assumed as a big number

Decision variables are considered as follows:

T_j^* Optimal replacement age of machine j

R^* Required number of repairmen in the shop floor r   Number of hired repairmen in the shop floor

$x_{iki'k'}$ 1, if O_{ik} is executed before operation $O_{i'k'}$, 0 otherwise

y_{jik} 1, if operation O_{ik} is assigned to the j^{th} machine, 0 otherwise

Random variables are defined as follows:

C_i Completion time of job i

C_{ik} Completion time of operation O_{ik}

B_{ik} Beginning time of operation O_{ik}

id_j The total idle time of machine j

pt_j The total processing time of machine j

In the mathematical model, the objective is to minimize the total cost of hiring repairmen, cost of energy consumption, and tardiness penalties. To incorporate energy consumption in the scheduling, the cost of energy usage in regard to different states of the machines, namely, operation and idle is considered in the objective function.

$$Min\ \ Z = r.C_{RM} + Max\left\{g_i\left[\sum_{i=1}^{n} y_{jn_ik}\ C_i - \ D_i\right],\ 0\right\}+\sum_{j=1}^{m} y_{jik}\left(\ e_{idle}^{j}\ .id_j +\ e_{run}^{j}\ .pt_j\right)$$

The constraint sets (1-9) which are needed in this model are given below.

$$r \leq R; R\ \in \{1,2, \dots, m\} \tag{1}$$

Besides the general constraints in FJSP, new constraints associated with the total number of repairmen in the manufacturing system is added to the model. Constraint (1) ensures that the number of hired repairmen in the shop floor is less than the total number of available repairmen for the system.

$$\sum_j y_{jik} = 1\ ; \quad \forall\ i, k \tag{2}$$

Constraint (2) assigns operations of the jobs on exactly one machine.

$$B_{ik} +\ \sum_j y_{jik}\ p_{ik}^{j}\ \leq B_{i\,(k+1)}\ ;\ \ \forall i, k\ = 1,2, \dots, n_i - 1 \tag{3}$$

Constraint (3) ensures the precedence relationship of consecutive operations for a job.

$$B_{ik} \geq B_{i'k'} + p^{j}_{i'k'} - H\left(2 - y_{jik} - y_{ji'k'} + x_{iki'k'}\right); \forall\, k, k';\ (O_{ik} \neq O_{i'k'}) \qquad (4)$$

$$B_{i'k'} \geq B_{ik} + p^{j}_{ik} - H\left(3 - y_{jik} - y_{ji'k'} - x_{iki'k'}\right); \forall\, k, k';\ (O_{ik} \neq O_{i'k'}) \qquad (5)$$

Each machine can be assigned at most one operation either O_{ij} or $O_{i'j'}$ in order to prevent overlap in the machines, according to the constraint (4) and (5); the value of $x_{iki'k'}$ can be determined in scheduling two operations of O_{ij} and $O_{i'j'}$ on machine j.

$$B_{ik} + \sum_j p^{j}_{ik}\ y_{jik} \leq C_{ik}; \quad \forall i \qquad (6)$$

Constraint (6) specifies that the starting time plus processing time of operation are less than or equal to the completion time of that operation.

$$B_{in_i} + \sum_j p^{j}_{in_i}\, y_{jik} \leq C_i; \quad \forall i \qquad (7)$$

Equation (7) is related to the completion time of each job which is determined based on the last operation of all the given jobs in the production system.

$$x_{iki'k'} \in \{0,1\} \qquad \forall j, i, k, i', k' \qquad (8)$$

$$y_{jik} \in \{0,1\} \qquad \forall j, i, k \qquad (9)$$

Constraints (8) and (9) define the binary natures of the decision variables of the model.

3.3 Simulation algorithm

This study addresses the joint production and PM scheduling in a flexible job shop environment. FJSP under uncertainty condition, more precisely, under machine breakdown, is more complicated than the one to be resolved in deterministic environments (He, Sun, & Liao, 2013); as a result, presenting the analytical solution is computationally unattainable. In stochastic FJSP, it is inevitable to use simulation-based optimization to solve the developed model. Steps of the applied simulation-based optimization model are described as follows: at the first phase, we determine the optimal replacement age for each machine as follows (Park, 1979):

$$T_j^* = \eta_j \left(\frac{C_{RP}^j}{(\beta_j - 1)C_M^j}\right)^{1/\beta_j} \tag{10}$$

At this point, we use the obtained optimal replacement ages of the machines for joint optimization of the production schedule and the maintenance operations. In the maintenance scheme, a number of random failures are generated for loaded machines. The failure process follows a non-homogenous Poisson process (NHPP). For the simulation model, the generated failure time depends on the current age, Weibull shape parameter, and Weibull scale parameter of the machine. The formula for generating the next failure time is based on equation (11), as follows:

$$\text{Next failure time} = \eta \left[\left(\frac{\text{Current age}}{\eta}\right)^{\beta} - \log(\mathrm{u})\right]^{1/\beta} - \text{Current age} \tag{11}$$

where u is a random number with uniform distribution $\big((u = uniform\ (0{,}1)\big)$.

We simulate the effect of machines' unexpected breakdowns on production schedules and maintenance. In fact, when applying a threshold-based maintenance policy, in case of occurring failure, the required maintenance action is divided into two categories: minimal repair or replacement activities. Upon exceeding this threshold at failure time, the machine is replaced and the operation is reprocessed (non-resumable) after replacement. While the age at failure is below the threshold of the given machine, the machine is minimally repaired and the interrupted process is resumable. Furthermore, when the age at which failure occurs is more than the defined threshold minus shift-threshold, we decide on the replacement of the machine. Another point is that if a repairman is available in the site for a maintenance task, an operation ends on the machine, and the age of the machine exceeds the threshold minus threshold-shift, the machine is preventively replaced. The flowchart in Figure 3.1 shows when maintenance actions must be conducted.

In the case when a failure takes place, and there is not any repairman on the shop floor, then the system incurs the cost of hiring a repairman together with traveling time. In the other case when there is a repairman in the system and a failure occurs, we have to compare the remaining time of his task to call in another repairman that imposes traveling time to the system.

We use two algorithms for the optimization scheme, which are GA and SA. The reason why we chose these algorithms is their popularity in solving combinatorial optimization problem, and most importantly, their superior performance in solving related problems as reported by Gao et al., 2006, Amjad et al., 2018, and Zandieh et al., 2017. This developed simulation-based optimization model provides an integrated plan of production schedules and maintenance activities that minimizes the total expected cost, which is the output of simulation.

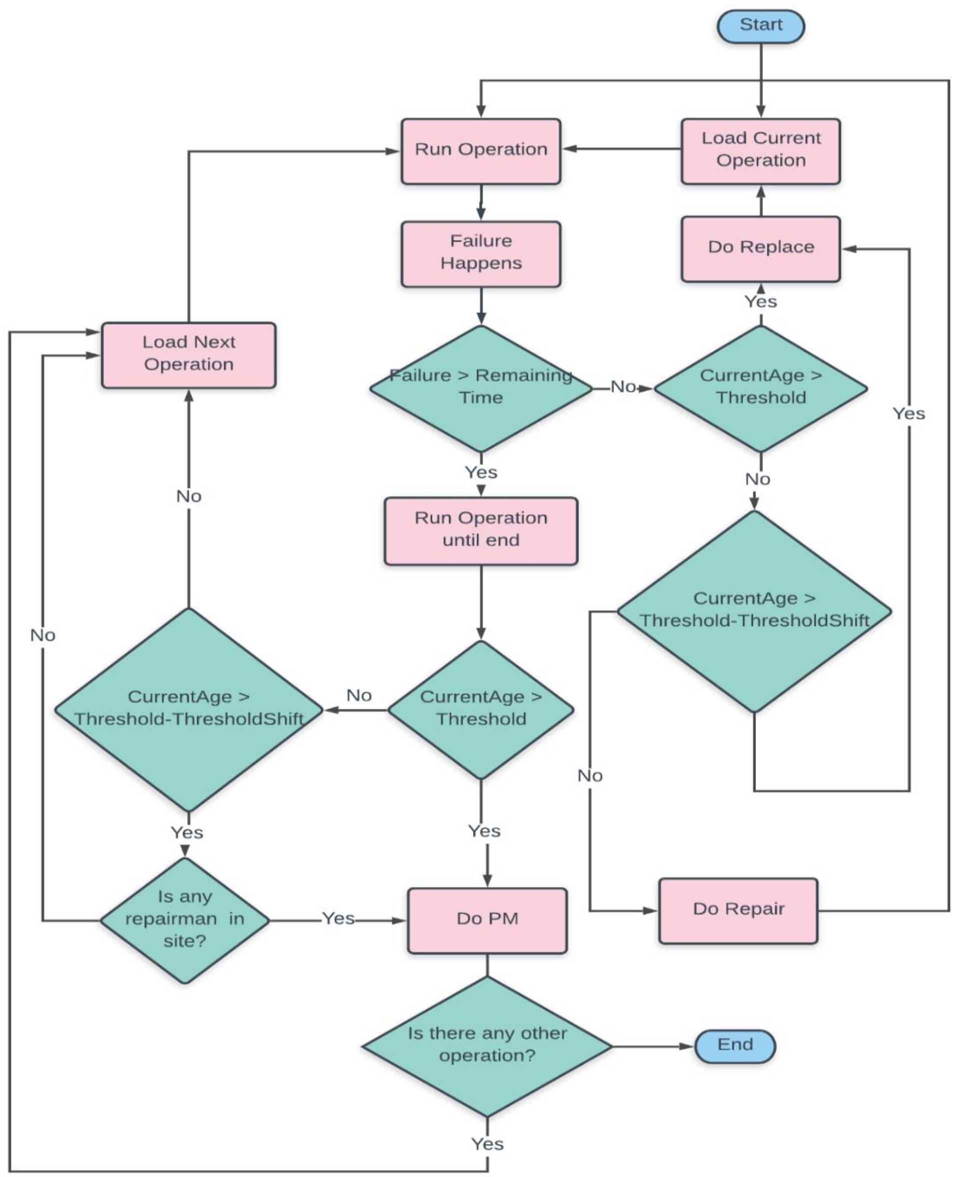

Figure 3.1 Schematic representation of conducting maintenance actions

4. RESULTS AND DISCUSSION

4.1 Proposed algorithms

Although exact methods ensure that there will be no better solution after solving a problem, the scope for using them is limited due to the complexity and computational burden of the FJSP (Amjad et al., 2018). Initially, to solve a FJSP with only two jobs and two machines, each job contains 2 operations, the solution space consists of $(\sum_i n_i + m - 1)! = 5!$. By adding a new constraint of maintenance crew limitation, this solution space multiplies by the maximum number of repairmen, $5! \times 2$. Then, by considering threshold-shift in order to perform be opportunistic maintenance, the solution space multiplied by the total number of threshold-shift plus one (when there is no threshold-shift); in our case, we consider $0, 1, \dots, 5$ threshold-shift, so the solution space accounts for $5! \times 2 \times 6$ totally. In such a problem, due to the extremely large solution space, meta-heuristics are the common approaches for finding satisfactory solutions in a reasonable time.

This study applies a genetic algorithm (GA) and a simulated annealing (SA) to obtain near-optimal solutions. Numerical examples are presented to illustrate how this approach works, and the performances of the GA and the SA are evaluated. Generally, the computational results and comparisons indicate that the GA is more effective in all cases.

4.1.1 Genetic algorithm

GA is a local search algorithm that is applicable to both discrete and continuous optimization problems (Naderi et al., 2009). Since introducing the GAs, a stochastic search method, by Holland in 1975, they have been recognized as capable and prevalent optimization approaches for constrained and combinatorial optimization problems [(J. Li et al., 2010), (Wang & Yu, 2010)]. Considering this fact, GAs have been widely adopted to solve production scheduling and maintenance planning, as proven by the increasing number of research on this topic (Pezzella et al., 2008)(Pezzella et al., 2008). Recently, Amjad et al. (2018) provided a comprehensive review of the FJSPs solved by the hybrid GA (hGA) techniques. In this study, we also opt to using the GA to solve energy-efficient FJSP and maintenance planning under maintenance crew constraint.

The fundamental underlying mechanism is to start from an initial population, and these solutions are encoded into chromosomes. At each generation (iteration), every new individual, namely, chromosome corresponds to a solution, in our case, a schedule of operations on machines (Driss, Mouss, & Laggoun, 2015). Additionally, GAs use two major operators, that is, crossover and mutation, to direct the population towards the global optimal solution iteratively (Driss et al., 2015). To describe more, after the selection and evaluation of the initial population, crossover empowers swapping information between various chromosomes, and mutation expands the population diversity. It is important to mention that the selection process is a primary operator that functions in a straightforward way: two random chromosomes are selected as parents for applying crossover and mutation operators (Taylor, May, Stahl, Taisch, & Prabhu, 2015). To this end, the roulette wheel strategy, as a well-known, functional selection procedure, is applied. In a roulette wheel selection, the probability of choosing an individual depends on its fitness. The whole process is on-going until a termination criterion has been reached.

The overall procedure of the adapted algorithm for the GA can be described as follows. As mentioned before, each chromosome represents a possible solution to the problem, and a chromosome is constituted by genes expressing the information of the problem. In our case, for encoding the production scheduling scheme, a string of S is defined with the size of $\sum_i n_i + m - 1$, where $\sum_i n_i$ is the total number of all operations of the jobs and m indicates the number of the machines in the system. Each chromosome states a solution for two sub-problems of scheduling, sequencing and assigning, simultaneously. In order to clearly describe, the integer numbers in the domain $[1, n_1]$ belong to operations of the job one, the integer numbers in the domain $[n_1 + 1, n_1 + n_2]$ belong to operations of the job two, and finally the integer numbers in the domain $[n_{n-1} + 1, n_{n-1} + n_n]$ indicate the operations of the n^{th} job. In addition, there are $m - 1$ numbers in a chromosome that their values are greater than $\sum_i n_i$ use as a separator to assign operations to the machines.

The procedures of encoding and decoding are illustrated by the following example. Suppose a shop has 3 machines and 4 jobs are required to operate; jobs 1, 2, 4 consist of two operations and job 3 has three operations to be processed. The proposed algorithm has been produced for the scheduling problem and the results are depicted in Figure 4.1 and Figure 4.2. Importantly, all the randomly generated offspring are feasible solutions that satisfy all the constraints, including the precedence constraints. To illustrate the point, in the string S, genes $\{1,2\} \in i = 1,\ \{3,4\} \in i = 2,\ \{5,6,7\} \in i = 3,\ and\ \{8,9\} \in i = 4$; in this case, the number attributed to each job that appears first demonstrates the first operation of the given job.

			Separator of Machine 1 &2 ↓				*Separator of Machines 2 & 3* ↓			
5	9	7	10	8	6	3	11	1	2	4
↑ $1^{st} operation\ of\ job$ 3		↑ 2^{nd} $operation\ of\ job$ 3			↑ $3^{rd} operation\ of\ job$3					

Figure 4.1 Encoding scheme of string S

A chromosome	5	9	7	**10**	8	6	3	**11**	1	2	4
Assignment	Operations assigned on machine 1				Operations assigned on machine 2				Operations assigned on machine 3		
Sequencing	O_{31} →	O_{41} →	O_{32}		O_{42} →	O_{33} →	O_{21}		O_{11} →	O_{12} →	O_{22}

Figure 4.2 Results of scheduling example solved by the GA for one of the optimal scenarios (with three repairmen)

In the reproduction phase, once the mating individuals are selected, the crossover operator is applied to a pair of chromosomes with the purpose of exchanging information to create new offspring. Two of the frequently used crossovers are a single-point crossover and a two-point crossover. In this work, the single-point crossover is utilized for assigning and sequencing schemes on the machines. For the single-point crossover, a position of parent string is selected and the genes after the selected point are exchanged (Costa, 2018). Afterward, the mutation operator is utilized to improve genetic diversity in the population. In the mutation phase, a percentage of the population is randomly selected and subjected to one of the mutation operators, that is, swap, reversion, and insertion with an equal probability to generate new individuals for scheduling problems (Fig. 4.3). A maximum number of iterations are considered as the stopping criterion of the algorithm.

Individual	1	2	3	**4**	5	6	**7**	8	9	10	11
(a)Swap offspring	1	2	3	7	5	6	4	8	9	10	11
(b)Reversion offspring	1	2	3	7	6	5	4	8	9	10	11
(c)Insertion offspring	1	2	3	7	4	5	6	8	9	10	11

Figure 4.3 An illustration of mutation operators

Based on the main operation described above, the underlying procedure of the proposed GA is depicted in Figure 4.4.

Pseudo-code of GA algorithm

Step 1: Initialize GA parameters and population

Step 2: Evaluate the population base on simulation

Step 3: Implement the crossover and mutation operations

Step 4: Re-evaluating the derived chromosomes

Step 5: Merging population

Step 6: Is the termination criteria met?

1) No, go to step 2.
2) Yes, go to step 7.

Step 7: The best solution

Figure 4.4 Pseudo-code of the GA algorithm

4.1.2 Simulated Annealing algorithm

Simulated annealing (SA) is a local search method used to solve the combinatorial optimization problems, and it was established by Kirkpatrick et al (1983). This stochastic searching algorithm is derived from an algorithmic analogy with the annealing of materials where the motive is to lead the material to a solid condition. In fact, the thermodynamic cooling process is continued until the system freezes to a steady-state. A control parameter named temperature, T, is used to guide the iterations. The basic idea of this algorithm can be described as follows: initially, the temperature begins at a high value, T_0 and it decreases slowly after a certain amount of iterations. As the temperature reduces according to a cooling rate ($0 < \propto < 1$), neighbor x' of the current solution x is found; it is acceptable if its solution results in a better objective function value. If the solution is worse than the current one, it is accepted as the new solution for the next iteration with probability $e^{-\triangle/T}$, where $\triangle = f(x') - f(x)$. The mechanism of accepting inferior solutions allows the SA to escape from a local optimum. The pseudo code of SA describes in Figure 4.5.

Pseudo-code of SA algorithm

Step 1: Initialize temperature

Step 2: Generate random solution x and evaluate f(x)

Step 3: Update x_{best}; $x_{best} = x$

Step 4: While stopping criteria are not satisfied:

  Create a neighbor solution x' and evaluate $f(x')$

  Accept x' with a probability of $p = e^{-\triangle/T}$

  If x is better than x_{best} , store x in x_{best}

  Reduce temperature

Step 5: End while

Figure 4.5 Pseudo-code of the SA algorithm

4.2 Computational Results

In this section, in order to verify the validity of our proposed mathematical model and solution algorithms, we design a numerical example. The proposed GA and SA were developed/coded in MATLAB R2015a, and run for 10 times on a computer with a Core i7(@2.40Hz) CPU and 8 GB RAM, and an operating system of Windows 10.

4.2.1 The test problem

A small sized production system in the flexible job shop environment illustrates how the proposed model is applied. There are four jobs to be done on three machines. The number of operations for each job, processing time of each operation, and other features of this example are given in Table 4.1, 4.2, and 4.3. This case study is an extension to our problem solved in Mirahmadi and Taghipour (2019).

Table 4.1 Operations' processing times (Unit time) (Mirahmadi & Taghipour, 2019)

Jobs	Operations	Machines	Processing times
Job 1	O_{11}	(M_1, M_2, M_3)	(15,10,12)
	O_{12}	(M_1, M_2, M_3)	(50,55,47)
Job 2	O_{21}	(M_1, M_2, M_3)	(40,35,35)
	O_{22}	(M_1, M_2, M_3)	(30,41,37)
Job 3	O_{31}	(M_1, M_2, M_3)	(7,7,8)
	O_{32}	(M_1, M_2, M_3)	(35,34,30)
	O_{33}	(M_1, M_2, M_3)	(16,14,15)
Job 4	O_{41}	(M_1, M_2, M_3)	(15,19,14)
	O_{42}	(M_1, M_2, M_3)	(21,26,22)

Table 4.2 The machine parameters for the numerical example

Machines	D_{MR}^j (Unit time)	D_{RP}^j (Unit time)	D_{PR}^j (Unit time)	C_M^j	C_{RP}^j	e_{idle}^j	e_{run}^j	η_j	β_j	T_j^*

M_1	0.2	0.5	0.4	2	8	1	6	50	1.7	139.39
M_2	0.3	0.6	0.5	3	10	2	8	60	1.7	150.26
M_3	0.3	0.5	0.5	4	7	1	7	55	1.8	84.96

e_{idle}^{j}= Unit energy cost of the machine in idle mode

e_{run}^{j}= Unit energy cost of the machine in operation mode

Table 4.3 Jobs parameters for the numerical example

Jobs	$i = 1$	$i = 2$	$i = 3$	$i = 4$
D_i (Due date of job i)	75	90	68	52
g_i (Penalty coefficient of job i)	20	10	20	20

4.2.2 Results

For initialization in a GA, the algorithm needs different variables related to itself and to the production system, such as, the size of the population, the crossover probability, the mutation probability, total number of jobs and machines, total number of operations of each job, duration of each operation of jobs, and energy consumption of each machine in working and idle states. The parameter values of the algorithm are as follows: crossover rate, mutation rate, population size, and termination criterion (iteration) are 0.7, 0.3, 50, and 150, respectively.

The simulated annealing algorithm comprises a series of iterations. In each iteration, a new solution (neighbor) is created in the neighborhood of the current solution. In this phase, the new solution is generated equally random choices from the swap, reversion, and insertion method in each temperature. A new solution is evaluated to accept as the current solution based on the cost function. In the underlying procedure in designing a SA algorithm, four parameters must be defined:

- An initial temperature (T_0)
- A cooling rate ($\propto$)
- The number of iterations that takes place at each temperature

- A stopping criterion for the search

The encoding scheme used is the same one used for the GA. Moreover, the results of this search procedure when $T_0 = 0.025$, $\propto = 0.99$, maximum number of iterations is 250, the maximum number of iterations at each temperature is 20, and the number of evaluations is fixed to 5000 in SA. As shown in Table 4.4, the results of GA demonstrate better performance than SA. We consider C_{RM} (cost of hiring a repairman) is 50 and the travel time of the repairman to the shop floor equals 1. The average cost results from 5 times run the algorithm.

Table 4.4 The results of scheduling with maintenance crew limitation for GA and SA

Threshold shift (Unit time)	r	GA			SA		
		R^*	The average cost	Standard deviation	R^*	The average cost	Standard deviation
0	1	1	1684.6	56.37	1	1721.2	98.98
	2	2	1713.4	97.79	2	1778.2	67.46
	3	2	1739	62.05	2	1787	76.71

R^* =Max required number of repairmen in all runs

As shown in Table 4.4, the average cost values are compared for three scenarios in both GA and SA. The average cost in the case of one repairman in the GA yields the best result.

4.2.3 The effects of the threshold shift and maintenance crew

For scheduling maintenance activities, fifteen scenarios are described and the obtained results are compared. Regarding the maintenance strategy, we consider five different threshold-shifts in the shop; then, for each threshold-shift here, we have three possible scenarios, $1 \leq r \leq m$, for the maintenance crew. In the first scenario, we solve the model with only one available maintenance crew in the system. In the second scenario, we consider the same example with restriction of maintenance crew availability where two repairmen are available in the system. In the last scenario, we have the maximum number of maintenance crew which equals the number of machines on the shop floor. For any scenario, the total cost, which encompasses the cost of energy consumption, tardiness penalty, and hiring a repairman in the shop floor, is calculated.

4.2.3.1 Genetic Algorithm

Table 4.5 summarizes the results of all mentioned scenarios when the cost of hiring each repairman C_{RM} is 50, travel time equals1, and the expected average cost resulting from 5 times runs of the simulation.

Table 4.5 The results of scheduling with maintenance crew limitation and opportunistic maintenance in the system

Threshold shift (Unit time)	r	R^* (Max required number of repairmen in all runs)	The average cost	Standard deviation
1	1	1	1702.2	67.42
	2	2	1713.4	36.42
	3	3	1704.2	42.49
2	1	1	1730.6	90.66
	2	2	1685	42.15
	3	2	1729.6	71.73
3	1	1	1688	52.91
	2	2	1722.6	65.79
	3	2	1751.8	87.21
4	1	1	1712	78.50
	2	2	1707.8	69.46
	3	2	1745.2	107.82
5	1	1	1707	63.42
	2	2	1673.8	20.08
	3	2	1709.6	91.13

As can be seen in Figure 4.6, the expected average cost implies that threshold-shift=5 with r=2 in the scheduling system is optimal.

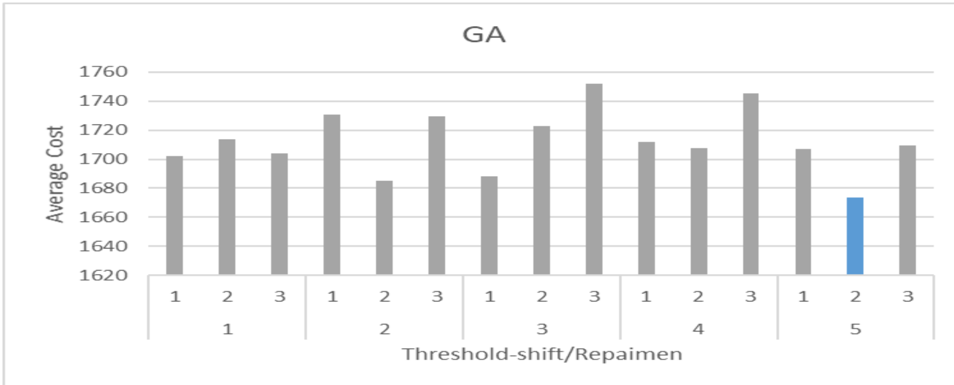

Figure 4.6 Detailed view of the average cost for different scenarios

Overall, after getting the results for the three scenarios for each threshold shift, we can see that having two repairmen in the system with five threshold shift incurs the least cost; Figure 4.7 depicts the convergence diagram of the scheduling problem for this case.

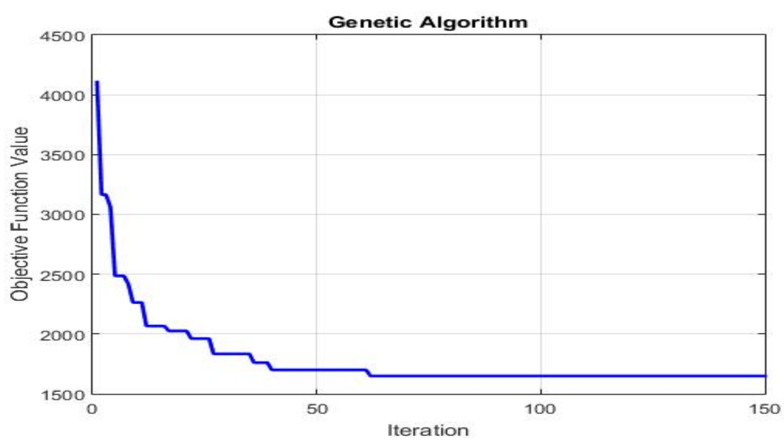

Figure 4.7 Convergence diagram of the GA with two repairmen and five threshold-shift for the best cost case

The expected total cost of the energy-aware FJSS and PM with consideration of the limited maintenance crew and the existing opportunistic maintenance strategy may result in a sub-optimal solution. According to the obtained results, we conclude that there are three maintenance plans that optimize the total expected cost including energy consumption, hiring maintenance staff, and due date penalty. On the whole, hiring a maintenance crew imposes a cost on a system, whereas planning to combine maintenance activities may result increase in the expected completion time of a job. Clearly, when a machine is waiting for the repairman, it still consumes energy like idle condition. So in our model, determining optimal solutions can minimize the cost of maintenance and energy while keeping the functional level of production based on the due date.

4.2.3.2 Simulated Annealing

The results of this search procedure when $T_0 = 0.025$, $\propto= 0.99$, and the number of evaluations is fixed to 5000 are shown in Table 4.6.

Table 4.6 The results of scheduling with maintenance crew limitation and opportunistic maintenance in the system

Threshold shift (Unit time)	r	R^* (Max required number of repairmen in all runs)	The average cost	Standard deviation
1	1	1	1709.8	52.39
	2	2	1707.4	70.34
	3	2	1819.2	68.31
2	1	1	1751.8	99.86
	2	2	1735.4	81.88
	3	2	1843.6	96.49
3	1	1	1672.4	33.78
	2	2	1686.2	76.53
	3	2	1759.2	78.50
4	1	1	1828.8	90.24
	2	2	1753.6	82.46
	3	2	1853.8	91.96
5	1	1	1760.4	93.99
	2	2	1761.6	102.16
	3	2	1819.2	82.15

According to the results of the expected average cost in 5 times runs the SA, it turns out that threshold-shift=3 with r=1 is optimal (Figure 4.8).

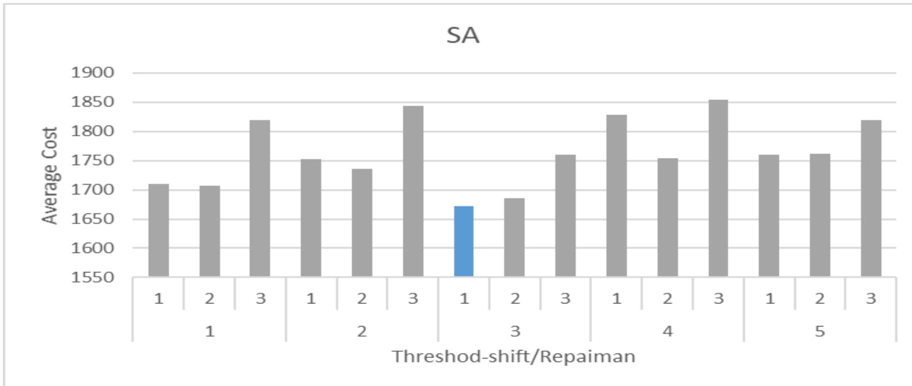

Figure 4.8 The obtained results of the SA

As an example, Figure 4.9 depicts the convergence diagram of the scheduling problem while there is one repairman in the site and we have three threshold-shift.

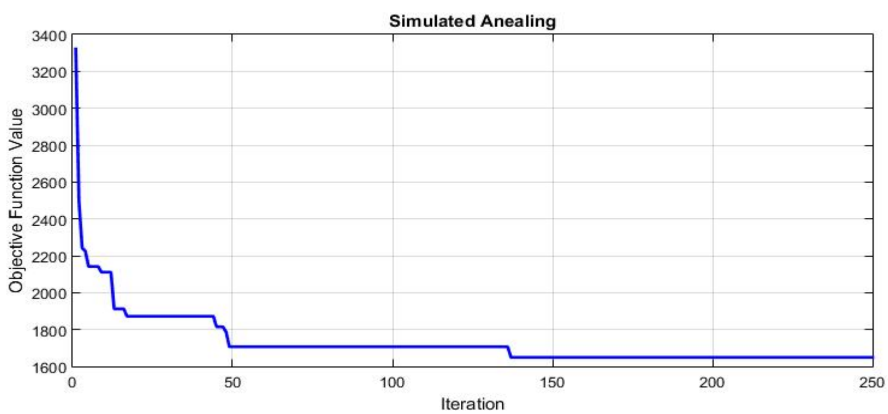

Figure 4.9 Convergence diagram of the SA with one repairmen and three threshold-shift for the best cost case

4.2.3.3 Comparison of SA and GA

Figure 4.10 illustrates the summary information of the algorithms. We fixed the number of evaluations for both algorithms to 5000, so there is no need to use the CPU time as a comparison criterion. According to the observation in this Figure, the genetic algorithm shows better performance compared to simulated annealing. In fact, GA outperforms SA in almost all cases, except the scenarios of three threshold-shift with $r = 1$ and $r = 2$ and one threshold-shift with $r = 2$ which SA performs better than GA.

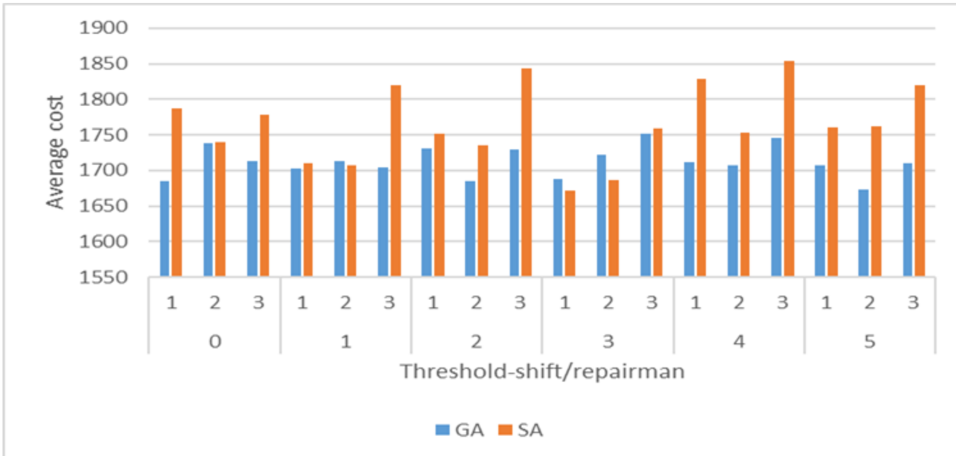

Figure 4.10 The graphical comparison of the algorithms

5. CONCLUSION AND FUTURE STUDIES

5.1 Conclusion

As energy and environment issues have become noticeably severe, sustainable development is the center of the entire activities in a production system (A. Jiang, Dong, Tam, & Lyu, 2018). Despite this, reasonable production and maintenance schedules have been proven to be a cost-effective approach in shrinking energy consumption of manufacturing shops. In this thesis, comprehensive literature on the existing mathematical model which has been done for the FJSP was provided. Then the relevant literature on energy-efficient scheduling was conducted. Finally, the literature review of the joint production and maintenance planning problem was considered, and this review was further classified in single-machine, parallel-machine, flow-shop, job shop, and flexible job shop scheduling problems. There is still a significant gap left for production-maintenance planning to make it consistent with reality, according to presented literature and summarization. Next, the problem of this thesis was examined in detail and the model was fully investigated. The thesis then continued to look at the simulation description, results of the GA and the SA and evaluation of the performance of them, and finally, the effect of the threshold and maintenance crew was presented.

This thesis investigated the production-maintenance scheduling in a flexible job shop environment where machines may be unavailable due to machine breakdown or PM activities. Due to the complexity of the problem, we used simulation-based optimization, where the optimized assignment and sequencing operation were subject to the random breakdowns of machines for the loaded ones. At this stage, we applied the optimal replacement age policy for maintenance operations. Besides the conventional constraints existing in the flexible job shop context, the proposed model is also considered maintenance crew constraint in the mathematical formulation and simulation. The aim is to minimize the total cost of hiring repairmen, energy consumption, and tardiness penalties.

In order to maintain a satisfactory level of availability of the shop floor machines, we incorporate the optimal age-based maintenance policy. In this policy, an optimal age for a replacement for each machine is calculated and scheduled PM is performed after completing an operation in the case that the age of the machine exceeds the defined optimal age. The case is different when a repairman is in the site; if the age of the machine passes the optimal age minus threshold-shift and an operation ends, we use opportunistic maintenance in the shop floor. Accordingly, depending on the age of the machine at failure time and its optimal replacement age, we carry out minimal repair or replacement that leads to an increase in the expected completion time of the jobs, which may impose tardiness penalties on the company. If the age of the failed machine surpasses the optimal replacement age, we will replace it, otherwise, we will perform the minimal repair.

Additionally, another aim of this research is to find the optimal number of the maintenance crew to minimize the total cost and improve the overall performance of the schedule. Afterward, in the presence of uncertainty related to machine failure, this NP-hard problem is more complex to solve, so a genetic algorithm (GA) and a simulated annealing (SA) are applied and their obtained results are compared. From an operation management viewpoint, the proposed model provides a scientific and helpful guideline for a manufacturing system to plan production and maintenance simultaneously, with both economic and environmental benefits.

5.2 Future studies

The proposed approach considers the integrated production-maintenance schedule incorporated with energy consumption issues. However, to maintain a more realistic industrial environment, here are some improvements which can be made in future research studies:

I. A mathematical model can be presented as a stochastic one to capture the uncertain nature of the shop floors in the real world by relaxing some assumptions or by considering a simpler scheduling problem.

II. The proposed maintenance policy can be considered in different industrial workshops, such as flow shops.

III. The approach can be developed by adding other aspects of uncertainty in the assumptions of the model such as new job arrivals or job cancellations during the scheduling horizon.

IV. This work proposes a derivative from age-based PM and opportunistic maintenance. However, various maintenance actions can be performed to slow down the degradation of machines like predictive maintenance planning.

V. This research can be extended by considering more than one objective to be optimized as well as considering the energy consumption of machines in different states of processing, idle, and setup.

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