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A Q-Learning Rescheduling Approach to the Flexible Job Shop Problem Combining Energy and Productivity Objectives

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Abstract: The flexible job shop problem (FJSP) has been studied in recent decades due to its dynamic and uncertain nature. Responding to a system's perturbation in an intelligent way and with minimum energy consumption variation is an important matter. Fortunately, thanks to the development of artificial intelligence and machine learning, a lot of researchers are using these new techniques to solve the rescheduling problem in a flexible job shop. Reinforcement learning, which is a popular approach in artificial intelligence, is often used in rescheduling. This article presents a Q-learning rescheduling approach to the flexible job shop problem combining energy and productivity objectives in a context of machine failure. First, a genetic algorithm was adopted to generate the initial predictive schedule, and then rescheduling strategies were developed to handle machine failures. As the system should be capable of reacting quickly to unexpected events, a multi-objective Q-learning algorithm is proposed and trained to select the optimal rescheduling methods that minimize the makespan and the energy consumption variation at the same time. This approach was conducted on benchmark instances to evaluate its performance.

Keywords: flexible job shop problem; artificial intelligence; rescheduling; Q-learning; machine failure; multi-objective optimization

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1. Introduction

Energy consumption control is a growing concern in all industrial sectors. Controlling the energy consumption and realizing energy savings are the goals of many manufacturing enterprises. Therefore, the scheduling of a manufacturing production system must now be approached taking into account aspects relating to sustainability and energy management [1]. To implement such measures, researchers focused on developing more energy-efficient scheduling approaches to make a balance between energy consumption and system stability. In addition to that, manufacturing systems constitute dynamic environments in which several perturbations can arise. Such disturbances have negative impacts on energy consumption and system robustness and make the scheduling process much more difficult. In the literature, a lot of researchers solve the job shop problem (JSP) under different types of perturbations, they use different metaheuristics approaches like genetic algorithms [2] or particle swarm optimization [3]. Other researchers use rescheduling approaches that repair the initial disrupted schedule Like dispatching rules.

Recently, many researchers have designed reactive, dynamic, and robust rescheduling approaches using artificial intelligence. These learning-based approaches gain the knowledge of the manufacturing system to be used in the decision-making process. In this case, the rescheduling can adapt to the system's disruption at any time. Research on reducing energy consumption in job shops has focused on energy consumption optimization in the predictive phase when building the initial schedule. The main contribution of this article is first to develop a new approach where energy consumption reduction is taken into account in the predictive and reactive phase. Second, the developed approach integrates a multi-objective machine learning algorithm to be able to react more quickly in case of disruptions (select best rescheduling method rapidly). In the predictive phase, a genetic algorithm was set to build the initial schedule, taking into consideration both energy consumption and completion time optimization. Then, to get a responsive and energy-efficient production system, a multi-objective Q-learning algorithm was developed. This algorithm selects the best rescheduling strategy that minimizes both the completion time and energy consumption in real time, depending on energy availability.

The remainder of this article is organized as follows: the next section provides a literature review on energy-aware scheduling and rescheduling methods, as well as rescheduling approaches using artificial intelligence techniques. Section 3 contains the FJSP problem formulation and the description of rescheduling methods. The Q-learning algorithm and selection of the optimal rescheduling approach are described in Section 4. The experiments and the evaluation of the approach on FJSP benchmarks are presented in Section 5. Finally, a conclusion and some future directions are provided.

2. Related Works

This section is divided into two parts. The first part presents some of the recent energy efficient methods for scheduling and rescheduling in manufacturing systems. The second part focuses on rescheduling methods using artificial intelligence (AI) techniques. A discussion section is presented to analyze the related works and to highlight their limits.

2.1. Energy-Efficient Scheduling

The approaches that can be found in literature are very often related to job shops or flexible job shops. The next subsections present a short overview of both problems.

2.1.1. Job Shop Energy-Efficient Scheduling

One of the most studied production scheduling problems in the literature is the job-shop scheduling problem (JSSP), in which jobs are assigned to resources at particular times. In recent years, due to rising energy costs and environmental concerns, researchers have started working on energy-efficient scheduling problems as a main feature of JSSP. Two integer programming models were for example used in [4], namely a disjunctive and a time-indexed formulation, to solve the JSSP in order to minimize electricity cost. A scheduling model with the turn off/turn on of machines was introduced in [5], and a multi-objective genetic algorithm based on non-dominated sorting genetic algorithm NSGA-II was developed to minimize the energy consumption and total weighted tardiness simultaneously. A metaheuristic to solve the JSSP which includes a power threshold that must not be exceeded over time was also developed [6], with two power requirements considered for operations: a peak consumption at the beginning of the machining and a nominal consumption after. The aim of this work was to minimize the makespan while respecting the power threshold. Decentralized systems attract the interest of many other researchers, where the decision making is distributed over several autonomous actors. For example, an agent-based approach for measuring, in real time, the energy consumption of resources in job shop manufacturing process [7], where the energy consumption was individually measured for each operation and the optimization problem was implemented using IBM ILOG OPL in order to minimize the makespan and the energy consumption.

2.1.2. Flexible Job Shop Energy-Efficient Scheduling

Another type of scheduling in job shop is the flexible job shop scheduling problem (FJSSP) as an extension of JSSP, which has been given widespread attention, due to its flexibility. An energy-efficient scheduling in FJSSP environment was designed by [8], with an enhanced evolutionary algorithm based on genetic algorithm and simulated annealing algorithms incorporated with three objective functions: minimizing total completion time, maximizing the total availability of the system, and minimizing the total energy cost. Similarly, an integrated energy and labor perception multi-objective FJSSP scheduling approach that considers makespan, total energy cost, total labor cost, maximal and total workload was proposed in [9]. In order to solve the optimization problem, the non-dominated sorting genetic algorithm-III (NSGA-III) was used. Likewise, in [10], a hybrid meta-heuristic algorithm based on an artificial immune algorithm (AIA) and simulated annealing algorithm (SA) was developed, to consider simultaneously the maximal completion time and the total energy consumption.

The aforementioned research handled the static scheduling, but few focused on the FJSSP under a real-life environment, considering disturbances such as machine failures, random and new arrival jobs, unexpected processing times or unavailability of operators. The accurate detection and control of these events is becoming a topic of concern on shop floors. The job-shop scheduling problem under disruptions that can occur at any time was solved by [11]. To achieve this, they used a match-up technique to determine the rescheduling zone and its feasible reschedule. Then, a memetic algorithm was proposed to find a schedule that minimizes the energy consumption within that zone. A rescheduling method based on a genetic algorithm to address dynamic events (i.e., new job arrivals and machine breakdowns) was introduced by [2]. The objective of their work was to minimize the energy consumption and the productivity simultaneously. Another form of unpredictable events that gets a lot of attention lately is the new job arrivals: [12] developed an energy-conscious FJSSP with new job arrivals, where the minimization of makespan and energy consumption and instability were considered. To solve the scheduling problem, they proposed a discrete improved backtracking search algorithm (BSA), and for the rescheduling they used a novel slack-based insertion algorithm. In [13], the authors designed a heuristic template for dispatching rules with a potential to make better routing decisions. As a solution, they developed a genetic programming hyper-heuristic with delayed routing (GPHH-DR) method for solving multi-objective DFJSS that optimizes the mean tardiness and energy efficiency simultaneously. Within this context and to deal with the new job arrival, [14] provided a dynamic energy aware job shop scheduling model which seeks a trade-off among the total tardiness, the energy cost and the disruption to the original schedule. An adequate renewed scheduling plan in a reasonable time, based on a parallel GA algorithm was presented. Scheduling of the energy-efficient FJSSP can also be settled with distributed approaches: [15] proposed a negotiation and cooperation-based information interaction and process control method, which combines IoT and energy-efficient scheduling methods, to quickly handle machine breakdowns and urgent order arrivals. In this study, a new metaheuristic algorithm, denoted as PN-ACO, based on timed transition Petri nets (TTPN) and ant colony optimization (ACO) algorithms, was introduced. An alternate form of metaheuristic algorithm for scheduling in FJSP is the particle swarm optimization method (PSO), which was used to minimize the makespan and global energy consumption under machine breakdowns in [3]. In [16], an evolved version of the PSO was presented, as well as a multi-agent architecture named EasySched for the predictive and reactive scheduling of production based on renewable energy availability.

2.2. *Job Shop Scheduling Using Artificial Intelligence*

After the emergence of artificial intelligence (AI) and machine learning (ML) techniques, intelligent and automated scheduling and rescheduling have become possible, and methods based on ML techniques began to arise. In general, there are three types of machine learning: supervised learning, unsupervised learning, and reinforcement learning. Starting with supervised learning techniques, the training data generally includes examples of the input vectors along with their corresponding target vectors [17]. In other terms, it is the learning of a function that maps an input to an output based on example input-output pairs. Decision tree (DT) is a well-known supervised technique used in literature: the scheduling knowledge can, for example, be modeled through data mining to identify a rule-set [18]. Three modules were designed here, namely optimization, simulation, and learning: (i) optimization provides efficient schedules based on tabu search (TS), (ii) simulation transforms the solution provided by the optimization module into a set of dispatching decisions and (iii) the learning module makes use of the implicit knowledge contained in the problem domain and efficient solution domain to approximate the behavior of efficient solution. Similarly, [19] applied a data mining module based on DT knowledge extraction. Here, timed Petri nets were used to describe the dispatching processes of JSSP, a Petri net-based branch-and-bound algorithm was used to generate efficient solutions, and finally the extracted knowledge was formulated as DTs and produced a new dispatching rule. This solution solved the conflicts between operations, by predicting which operation should be dispatched first. Another machine learning technique that combines several decision trees is random forest (RF). The authors in [20] started by generating and processing data samples of machine failures, then designed the RF-based rescheduling model that would decide which rescheduling strategy has to be made (no rescheduling, right-shift rescheduling or total rescheduling). In [21], a comparison between several machine learning techniques was made. They developed a model for the FJSSP with sequence-dependent setup and limited dual resources, solved the scheduling problem through a hybrid metaheuristic approach based on GA and TS to minimize the makespan, then trained the ML classification models such as support vector machines (SVM) and RF for identifying rescheduling patterns when machines and setup workers are not available.

A subset of supervised learning in literature is deep learning. In [22] GA was used to solve the scheduling problem in a job shop in order to minimize the makespan, coupled with an artificial neural network (ANN), which was employed to predict the total energy consumption. GA was also used in [23] to minimize the makespan, but they handled the dynamic events and perturbations in a job shop environment, they therefore designed a back-propagation neural network (BPNN) to describe machine breakdowns and new job arrivals. Thanks to their feedback adjustments, BPNN can generate a feasible solution for the JSP by resolving the conflicts. In [24] cumulative time error was used as the quantitative index of implicit disturbance, locally linear embedding (SLLE) and general regression neural networks (GRNN) were applied to reduce and map the data, and then a least square-support vector machine (LS-SVM) was used to select the best rescheduling mode.

Other works treated the new job arrival disturbance. The authors of [25] presented a scheduling and dispatching rule-based approach for solving a realistic FJSSP, through a combination of a discrete event simulation (DES) model and a BPNN model to find optimal or near-optimal solutions while favoring the fast reactivity to unexpected new arrival jobs. An appropriate management of both methods in the GA optimization process (GA-Opt) was achieved to minimize the makespan.

Compared with supervised learning, unsupervised learning operates upon only the input data without outputs or target variables. The goal in such problems may be to discover groups of similar examples within the data, in an operation called clustering [17]. K-means, an unsupervised technique, was used in [26]. They developed the modified variable neighborhood search (MVNS) method in the optimization process to minimize the mean flow time. This method was combined with the k-means algorithm as a cluster analysis algorithm. It was used to place similar jobs according to their processing time into the same clusters, then jobs in the farther clusters have greater probability to be selected in the replacement mechanism.

The third type of machine learning is reinforcement learning (RL). This type was widely used to solve the scheduling problem in job shop. It describes a class of problems where an agent operates in an environment and must learn to operate using feedback. The use of an environment means that there is no fixed training dataset. In other words, reinforcement learning is learning what to do, how to map situations to actions to maximize a numerical reward signal. The learner is not told which actions to take, but instead must discover which actions yield the most reward by trying them [27]. There are different types of reinforcement learning such as Q-learning, deep Q-learning, SARSA, policy gradient, prioritized experience replay … [28] are among the first ones to have used reinforcement learning in their work. They proposed an approach to learn local dispatching policies in a job shop with the aim of reducing the summed tardiness. They applied an ANN- based agent to each resource which was trained by Q-learning. This approach demonstrated a better performance than common heuristic dispatching rules. The authors of [29] developed a rule-driven dispatching method. To do so, they used reinforcement learning to train the intelligent agent in order to obtain the knowledge to set appropriate weight values of elementary rules to solve the work in process fluctuation of a machine. The objective of their work was to minimize the mean flow time and mean tardiness time in JSSP. In a different way of using RL, [30] used a policy gradient method for autonomous dispatching to minimize the makespan. They designed a multi-agent system where each machine was attached to an agent which employed probabilistic dispatching policies to decide which operation is currently waiting to be processed. In the same context, to select the best dispatching rule, in [31] the rescheduling strategy was acquired by the agent of the proposed Q-learning. The agent-based approach can then select a best strategy under different machine failures. In [32], the Q-learning algorithm was applied to update the parameters of the variable neighborhood search (VNS) at any rescheduling point. New job insertion was also handled using Q-learning. In [33], six composite dispatching rules were developed to select an unprocessed operation and assign it on an available machine when an operation is completed or a new job arrives. Later, a deep Q-learning agent was trained to select the appropriate dispatching rules. In a distributed way, [34] used a Q-learning algorithm associated with Intelligent Products (IP) which collected data to pinpoint the current scheduling context, and then determined the most suitable machine selection rule and dispatching rule in a dynamic flexible job shop scheduling problem with new job insertion. The authors of [35] proposed a multi-agent system containing machine, buffer, state and job agents for dynamic job shop scheduling to minimize earliness and tardiness punishment. A weighted Q-learning algorithm based on a dynamic greedy search was adopted to determine the optimal scheduling rules.

A comparison between all the above-mentioned studies is summarized in Table 1. The first column indicates the reference of the works, the second column specifies the type of problem studied, the third column defines the type of perturbation considered. In the fourth column, the scheduling or rescheduling method is presented. In the fifth and sixth column the solving method architecture is mentioned: centralized, which means that only one actor handles the scheduling problem, or distributed, through different communicating agents. In the seventh and eighth columns, the nature of the objective function and the objectives to minimize are presented. Finally, in the last column, the artificial intelligence techniques used in relevant works are presented.

2.3. Discussion

Most works in the literature consider energy-efficiency scheduling as a multi-objective strategy, which includes reducing the energy consumption or the energy cost alongside the traditional scheduling objectives, e.g., makespan, mean tardiness, mean flow time, maximal workload and many other objectives. Considering the energy related strategies and the traditional objectives proved to be a good solution to increase scheduling efficiency, this new technique is inspiring a lot of research and has become an important topic.

To reduce energy consumption, many aspects were reviewed. Processing, machine idle time reduction, machine speed, transportation, maintenance, setup and switching energy are examples of energy consumption aspects. Many articles handle the energy efficiency in scheduling but do not clearly outline the energy consumption aspects, or only consider one aspect, mainly the processing energy, and ignore the rest that can have a great impact on energy consumption.

Table 1. An overview of the literature review for energy-efficient scheduling.

Reference	Type of Problem	Type of Disturbance	Scheduling/ Rescheduling Techniques	Architecture		Objective Function		AI Techniques
				Centralized	Distributed	Mono-Objective	Multi-Objective	
[4]	JSP		Integer linear programming	×		Energy cost		
[5]	JSP		NSGA-II	×			Energy consumption And total weighted tardiness	
[6]	JSP		GRASP × ELS	×		Makespan		
[7]	JSP		IBM ILOG OPL: ILOG CP Optimizer		×		Makespan and energy consumption	
[8]	FJSP		Evolutionary algorithm	×			Total completion time; total availability of system; energy consumption	
[9]	FSJP		NSGA-III	×			Makespan; total energy cost; total labor cost; maximal workload; and total workload	
[10]	FJSP		hybrid meta-heuristic: AIA and SA	×			Maximal completion Time and total energy consumption	
[11]	JSP	Disruptions	match-up technique and memetic algorithm	×			Makespan and energy consumption	
[2]	FJSP	New jobs arrival and machine breakdown	GA	×			Energy consumption and schedule efficiency	
[12]	FJSP	New job arrivals	BSA with slack-based insertion strategy	×			Makespan, total energy consumption, and instability	
[13]	FJSP	New job arrivals	GPHH-DR	×			Mean tardiness and energy efficiency	
[14]	DJSP	New job arrivals	parallel GA	×			Total tardiness; total energy cost; disruption to the original schedule	
[15]	FJSP	Machine breakdown and urgent order arrival	PN-ACO + IOT		×	Energy consumption		
[3]	FJSP	Machine breakdowns	PSO	×			Makespan and Less global energy consumption	

Table 1. *Cont.*

Reference	Type of Problem	Type of Disturbance	Scheduling/ Rescheduling Techniques	Architecture		Objective Function		AI Techniques
				Centralized	Distributed	Mono-Objective	Multi-Objective	
[16]	FJSP	Machine breakdowns	PSO with editable ponderation factor		×		Makespan and energy consumption	
[28]	JSP				×	Summed tardiness		neural network + Q-learning
[22]	JSP		GA	×		Makespan		ANN
[29]	JSP	Fluctuation of WIP		×			Mean flow time and Mean tardiness	Q-learning
[30]	JSP				×	Makespan		Policy gradient
[18]	JSP		TS	×		Lateness		DT
[19]	JSP		Petri net-based branch-and-bound algorithm	×		Makespan		DT
[23]	DJSP	Machine breakdown and new job arrivals	GA	×		Makespan		BPNN
[24]	JSP	Recessive disturbances	RSR/PR/TR	×		Time accu-mulation error		SLLE + GRNN + LS-SVM
[20]	DJSP	Machine failure	RSR/TR	×		Delay and deviation		RF
[26]	DJSP	Random job arrivals and Machine breakdowns	MVNS	×		Mean flow time		k-means
[32]	DJSP	Random job arrivals and Machine breakdowns	VNS	×		Mean flow time		Q-learning
[31]	FJSP	Machine failure	GA	×		Makespan		Q-learning
[21]	FJSP	Availability of machines and setup workers	GA + TS	×		Makespan		ML classification
[25]	FJSP	New job insertions	GA-Opt	×		Makespan		BPNN
[33]	FSJP	New job insertions		×		Total tardiness		DQN
[34]	FSJP	New job insertions			×		Makespan; total weighted completion time;	Q-learning
[35]	JSP	New job insertions			×	Earliness and tardiness punishment		Q-learning
Our method	FJSP	Breakdown of machines	GA	×			Makespan, robustness and energy consumption	Multi-objective Q-learning

About rescheduling, many methods are dynamically used in job shops, but these methods depend on the state of the system in a particular moment. Due to the changing and uncertain nature of job shops, rules have to be modified dynamically and at the right time. Therefore, rescheduling can be handled using machine learning algorithms. In that case, the system is able to select the best method and adapt to the system's perturbation. The learning methods are trained to acquire the system's knowledge which will be used in the decision-making process. From the literature review, a lot of works applied these learning-based approaches using inductive learning, neural networks, or reinforcement learning, especially RL which has been widely used and has proved to have high performance in selecting the best approaches for rescheduling or modifying existing approaches. However, they have not integrated energy-efficiency in these approaches and are usually interested in minimizing the operations execution time. In this article both makespan and energy consumption reductions are considered in the learning process.

A classical GA was chosen for the initial solving of FJSSP (predictive phase). GAs have already been successfully adopted to solve FJSSP, as proven by the growing number of articles on the topic. Genetic algorithms might not be the best solution in a generic context in terms of solving time. However, this solving is performed in an offline phase that is not penalizing in the context of this work. Moreover, a different choice can be made by a practitioner according to a specific context, without questioning the validity of the overall approach.

On the reactive phase of rescheduling, as no prior knowledge of the environment is considered (because no coherent pre-trained data of manufacturing system were available to use in the learning process), Q-learning was chosen in this work. Literature provides many works that have used Q-learning for a single objective, optimization of productivity, whereas this article develops a multi-objective optimization that also considers energy consumption. In addition, the learning is generally performed on classical dispatching rules. This article presents a learning phase on actual multi-objective optimization methods of rescheduling.

In addition, Q-learning is an agent-based approach which facilitates its integration in distributed approaches that can be developed on embedded systems which is the topic of possible future works.

3. A Dynamic Flexible Job Shop Scheduling with Energy Consumption Optimization

The FJSSP has been widely researched in recent decades due to its complexity. On top of that, dynamic events can occur frequently and randomly in job shop systems, which increases its complexity. Many metaheuristics have been proposed in literature to solve this problem. In this section, a solution to FJSSP considering energy consumption optimization is proposed. Then, corresponding rescheduling methods are proposed to handle the dynamic nature of the system.

3.1. Description of FJSSP

In FJSSP, there are n jobs that should be processed on M machines. Each job consists of a predetermined sequence of n_j operations which should be processed in a certain order. The objective of FJSSP is to assign each operation to the suitable machine and arrange the sequence of operations on each machine [36].

We define the notations used in this article to model the FJSSP:

- $J = J_1 \ldots J_n$ is a set of n independent jobs to be scheduled.
- O_{ij} is the operation i of job j.
- $M = M_1 \ldots M_m$ is a set of m machines. We denote P_{ijk} the processing time of operation O_{ij} when executed on machine Mk.

FJSSP is a generalization of the job shop scheduling problem, where an operation can be processed on several machines, usually with varying costs. Here after a list of characteristics of FJSP problem:

1. Jobs are independent and no priorities are assigned to any job type.

2. Operations of different jobs are independent.
3. Each machine can process only one operation at a time.
4. Each operation can be processed without interruption during its performance on one of the set of machines.
5. There are no precedence constraints among operations of different jobs.
6. Two assumptions are considered in this work:
7. All machines are available at time 0 and the transportation time is neglected.

An example of an FJSSP instance is presented in Table 2. A processing machine and time of FJSSP includes 3 jobs and 4 machines.

Table 2. An instance of FJSSP.

Jobs	Operations	Processing Machine and Time (Time Units)			
		M1	***M2***	***M3***	***M4***
J1	O_{11}	3	5	-	7
	O_{21}	5	-	4	5
	O_{31}	9	12	8	10
J2	O_{12}	2	2	1	4
	O_{22}	-	-	-	9
	O_{32}	5	2	4	2
J3	O_{13}	-	5	6	5
	O_{23}	4	-	4	4
	O_{33}	5	6	8	-

A full description of the mathematical mixed integer programming (MIP) formulation for FJSP considering energy consumption proposed MIP has been proposed in [37].

Table 2 illustrates an example of a small FJSP instance.

3.2. Genetic Algorithm (GA)

In this article, we propose to use a classical GA for the initial solving of FJSSP [38]. It is an optimization method based on an evolutionary process. The performance validation of the proposed algorithm is detailed in Section 5.1.

The aim of the FJSSP is to find a feasible schedule that minimizes makespan and energy consumption at the same time. Therefore, makespan and energy consumption are integrated into one objective function (F) using a weighted sum approach. The relative importance of each objective can be modified in F, which represents the fitness of the GA. Since the values of energy consumption and makespan are not proportional, we have to normalize both measures [39]. As presented in equation 1, makespan is divided by MaxMakespan, which is the maximum makespan value for the given problem, and energy consumption is divided by the MaxEnergy, which is the sum of the energy needed to execute all tasks of the problem. λ is the weight that reflects the importance of each objective function, $\lambda \in [0 \ldots 1]$. This weight is modified statically, in this work. A dynamic evolution of λ is out of the scope of this article, and future perspectives may consider using an agent that controls the energy availability and triggers a rescheduling order when a threshold is reached.

$$F = \lambda \times \frac{makespan}{MaxMakespan} + (1 - \lambda) \times \frac{energy}{MaxEnergy} \tag{1}$$

A flow chart illustrating the process of the genetic algorithm is represented in Figure 1. The overall structure of GA can be described in the following steps:

1. Encoding: Each chromosome represents a solution for the problem. The genes of the chromosomes describe the assignment of operations to the machines, and the order in which they appear in the chromosome describes the sequence of operations.

2. Tuning: The GA includes some tuning parameters that greatly influence the algorithm performance such as the size of population, the number of generations, etc. Despite recent research efforts, the selection of the algorithm parameters remains empirical to a large extent. Several typical choices of the algorithm parameters are reported in [40,41].
3. Initial population: a set of initial solution is selected randomly.
4. Fitness evaluation: A fitness function is computed for each of the individuals, this parameter indicates the quality of the solution represented by the individuals.
5. Selection: At each iteration, the best chromosomes are chosen to produce their progeny.
6. Offspring generation: The new generation is obtained by applying genetic operators like crossover and mutation
7. Stop criterion: when a fixed number of generations is reached, the algorithm ends and the best chromosome, with their corresponding schedule, is given as output. Otherwise, the algorithm iterates again steps 3–5.

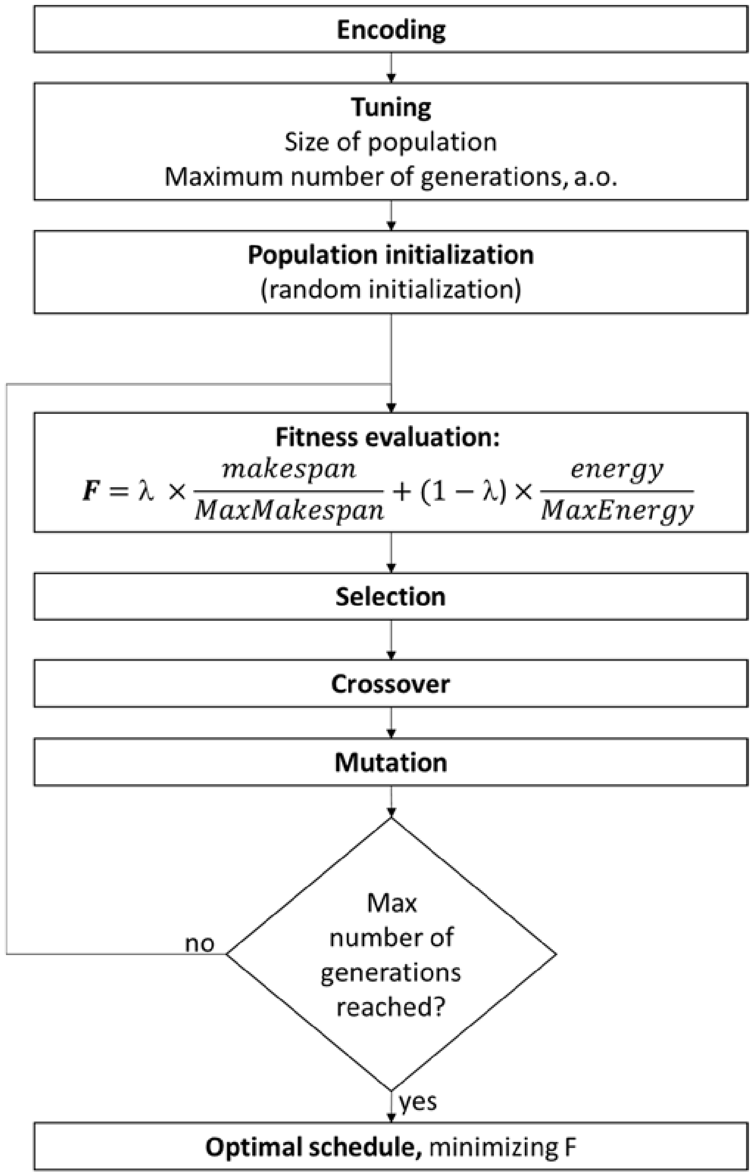


Figure 1. Genetic algorithm process.

3.3. Disturbances in FJSSP

FJSSP considers a large variety of disturbances. These perturbations are random and uncertain and will bring instability to the initial schedule. In this work, one of the most common and frequent disruption in production scheduling will be considered: machine failures. We will deal with these events using rescheduling methods that will be discussed in the next section. These methods will try to maintain the stability of the system.

To simulate a machine failure [3], we have to select:

- The moment when the failure occurs (rescheduling time). These failures are randomly occurring, with a uniform distribution between 0 and the makespan of the original schedule generated with GA algorithm.
- The machine failing.
- The breakdown duration, which obeys to a uniform distribution between 25% and 50% of the makespan.

To simplify the problem, some assumptions about machine failures are considered:

1. There is only one broken-down machine at a time.
2. The time taken to transfer a job from the broken-down machine to a properly functioning machine is neglected.
3. Machine maintenance is immediate after the failure.

3.4. Rescheduling Strategies

One question can arise when dealing with the system disturbances, or the changed production circumstances: what kind of rescheduling methodologies should be used to produce a new schedule for the disturbance scenario? In the literature, many rescheduling methodologies were reported. Researchers classified these methods into two categories: (i) repairing a schedule that has been disrupted and (ii) creating a schedule that is more robust with respect to disruptions [42,43].

There are common methods used to repair a schedule that is no longer feasible due to disruptions: right shifting rescheduling, partial rescheduling, and total rescheduling. Their definitions are described respectively as follows [24]:

- Right shifting rescheduling (RSR): postpone each remaining operation by the amount of time needed to make the schedule feasible.
- Partial rescheduling (PR): reschedule only the operations affected directly or indirectly by the disturbances and preserve the original schedule as much as possible.
- Total rescheduling (TR): reschedule the entire set of operations that are not processed before the rescheduling point.

The choice of the most appropriate methodology depends on the nature of the perturbation and is generally made by experts. Rescheduling methods have different advantages and drawbacks: RSR and PR can quickly respond to machines' breakdowns, however TR can offer a high-performance rescheduling, but with excessive computational effort. In this work, the targeted rescheduling strategy is the optimal one that minimizes the makespan and the energy consumption.

4. Proposed Multi Objective Q-Learning Rescheduling Approach

The proposed Q-learning-based rescheduling is described in Figure 2. The system is composed of two modes:

- An offline mode: in the first place the predictive schedule is obtained using a genetic algorithm, which represents the environment of the Q-learning agent. By interacting with this schedule and simulating experiments of machine failures, this agent learns how to select the optimal rescheduling solution for different states of the system.
- An online mode: when a machine failure occurs, the state of the system at the time of the interruption is delivered to the Q-learning agent. It responds by selecting the optimal rescheduling decision for this particular type of failure.

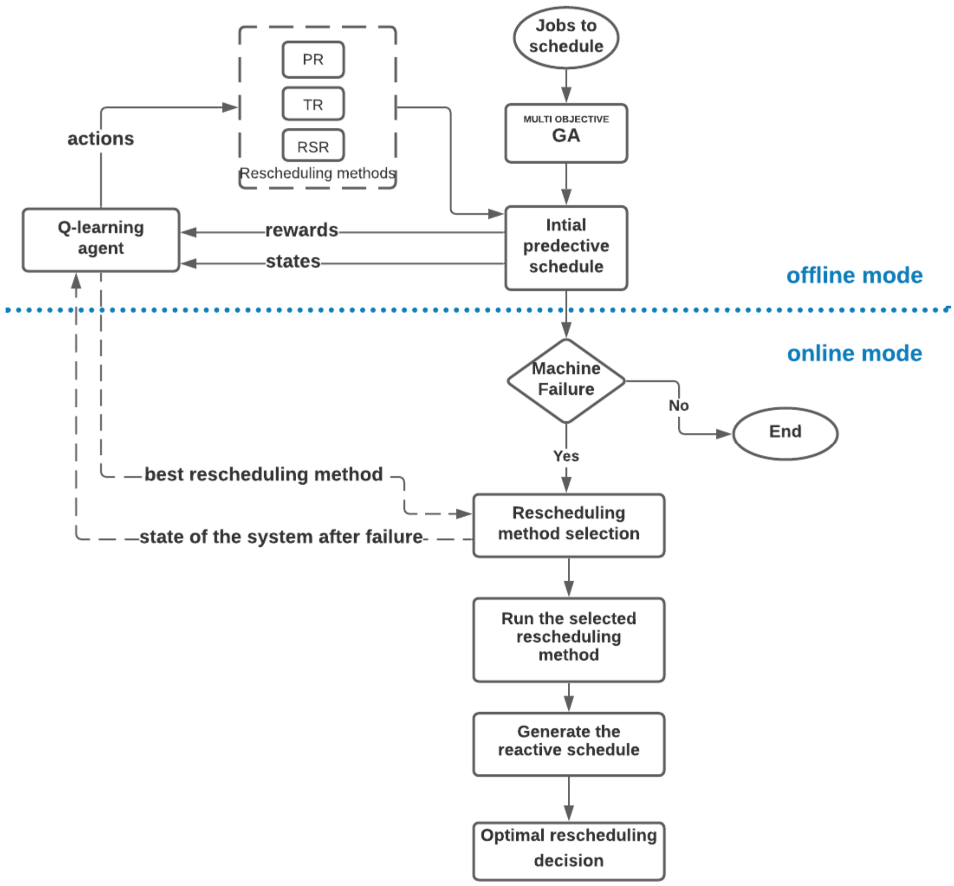


Figure 2. Proposed reschedule decision-making approach under machine failure.

A key aspect of RL is that an agent has to learn a proper behavior. This means that it modifies or acquires new behaviors and skills incrementally [44]. An improvement of the Q-learning algorithm was also made to consider different criteria (multi-objective Q-learning). Next sections detail this algorithm.

4.1. Q-Learning Terminologies

In order to be more accurate in the description of the algorithm, some terminologies of Q-learning are recalled below [45]:

- Agent: The agent interacts with its environment, selects its own actions, and responds to those actions;
- States: The set of environmental states S is defined as the finite set $\{s^1,\ldots, s^N\}$, where the size of the state space is N;
- Actions: The set of actions A is defined as the finite set $\{a^1,\ldots, a^k\}$, where the size of the action space is K. Actions can be used to control the system's state;
- Reward function: The reward function specifies rewards for being in a state or doing some action in a state.

To sum up, the agent will make optimal decisions using experiences, make an action in a particular state, and evaluate its consequences based on a reward. This process is done repeatedly until it becomes able to choose the best decision.

Q-learning is a value-based learning algorithm; it updates the value function based on a Bellman equation. The 'Q' here stands for quality of an action. The agent maintains a table of $Q(s, a)$, updated along time based on Equation (2):

$$Q(s_t, a_t) = (1-\alpha)\, Q(s_t, a_t) + \alpha\big(\, r_{t+1} + \gamma max Q(s_{t+1}, a\,)\big) \tag{2}$$

where r_{t+1} is the reward received when the agent transferring from the state s_t to the state s_{t+1}, α is the learning rate ($0 < \alpha \leq 1$) (representing the extent to which our Q-values are being updated in every iteration), and γ is the discount factor ($0 \leq \gamma \leq 1$) (determining what importance is given to future rewards).

The algorithm of Q-learning is detailed in Algorithm 1.

Algorithm 1 Q-Learning

Initialize $Q(s\ ,\ Aa\ )$ randomly
Repeat for each episode:
  Initialize s
  Repeat for each step of episode
    Choose an action from a using a policy derived from Q (ε-greedy)
    Take an action a and observe the reward R and the next state s′
    Update
      $Q(s_t ,a_t) = (1 - \alpha)\ Q(s_t ,a_t) + \alpha(\ r_{t+1} + \gamma maxQ(s_{t+1}\ , a\ ))$
    $s \leftarrow s'$
    until s is terminal

4.2. Multi-Objective Q-Learning

In this case the agent has to optimize two objective functions at the same time. Here, the reward will transform from a scalar value to a vector of the size of the number of objective functions:

$$R(s,\ a) = [R_1\,(s\ ,\ a\ ), R_2(s\ ,\ a\ )\ \ldots\ldots\ldots\ldots..R_m(s\ ,\ a\ )] \tag{3}$$

where m is the number of objective functions.

The same thing occurs with action-state value $Q(s,a)$ which becomes also a m-dimensional vector which is defined as follow:

$$Q(s,\ a) = [Q_1\,(s\ ,\ a\ ),\ Q_2(s\ ,\ a\ )\ \ldots\ldots\ldots\ldots..Q_m(s\ ,\ a\ )] \tag{4}$$

where every value corresponds to a reward value from the reward vector.

In this article a multi-objective Q-learning with single policy approach is used. This means that it reduces the dimensionality of the multi-objective function. This new function fairly represents the importance of all objectives. For the single policy approach, many methods have been proposed. The most well-known is the weighted sum approach where scalarizing function is applied to $Q(s, a)$ to acquire a scalar value $\overline{Q(s\ ,\ a\ )}$ that considers all the objective functions. The linear scalarizing function is used and described as follows:

$$\overline{Q(s\ ,\ a\ )} = \textstyle\sum_{i=0}^{m} Q_i(s\ ,\ a\ )] * w_i \tag{5}$$

where $0 \leq w_i \leq 1$ is the weight that specifies the importance of each objective function, and must satisfy the following equation: $\sum_{i=0}^{m} w_i = 1$

The algorithm of the multi-objective Q-learning is detailed in Algorithm 2.

Algorithm 2 Multi-Objective Q-Learning

Initialize $Q(s\ ,\ a\ )$ randomly
Repeat for each episode:
    Initialize s
    Repeat for each step of episode
      Choose an action from a using a policy derived from Q (ε-greedy)
      Take an action a and observe the rewards R_1 and R_2 and the next state s'
      Update
        $Q_1(s_t\,, a_t) = (1 - \alpha)\ Q_1\ (s_t\,, a_t) + \alpha(R_{1t+1}\ + \gamma\ maxQ_1\ (s_{t+1}\,, a\ ))$
        $Q_2(s_t, a_t) = (1 - \alpha)\ Q_2\ (s_t\,, a_t) + \alpha(R_{2t+1}\ + \gamma\ maxQ_2\ (s_{t+1}\,, a\ ))$
      $s \leftarrow s'$
      until s is terminal

4.3. State Space Definition

The state space is the set of all possible situations the agent could inhabit. We have to select the number of states that will give the optimal solution and how to define these states. In this article, two indicators were used to establish the state space:

- $s1$: indicates the moment when the perturbation happens, e.g., in the beginning, the middle or in the end of the schedule. For this purpose, the initial makespan was divided into 3 intervals, so $s1$ can take the values 0, 1 or 2.
- $s2$: defined by the indicator SD which is the ratio of the duration of the directly affected operation by the machine's breakdown to the total processing time of the remaining operations on failed machine. The formula is described as follows:

$$SD = \frac{O_{aff}}{RT} * 100 \tag{6}$$

where O_{aff} is the directly affected operation by the breakdown machine and RT is the total processing time of the remaining operations on failed machine. $s2$ is an integer between 0 and 9 depending on the value of SD.

The couple ($s1$, $s2$) represents the state of the system at a particular time, given the rescheduling time, the failure machine, and the breakdown duration. In total we have 30 states, where $0 \le s1 \le 2$ and $0 \le s2 \le 9$ ($s1$ and $s2$ are integers).

4.4. Actions and Reward Space Definition

The agent encounters one of the 30 states, and it takes an action. The action in this case is one of the rescheduling methods:

- Action 0: Partial rescheduling (PR)
- Action 1: Total rescheduling (TR)
- Action 2: Right shifting rescheduling (RSR)

The definition of the reward plays an important role in the algorithm since the Q-learning agent is reward-motivated. This means that it selects the best action by evaluating the reward. In this work, the reward is a vector with two scalars

$$R(s,\ a) = [R_1(s,\ a),\ R_2(s,\ a)] \tag{7}$$

where $R_1(s, a)$ depends on delay time (the longer the delays, the smaller the rewards) and $R_2(s, a)$ depends on the difference of energy consumption between the initial scheme and the scheme after rescheduling (the bigger these differences, the smaller the rewards). The rewards are set to be between 5 and -5, based on how much delay time there is and the difference in energy consumption the action will cause.

5. Experiments and Results

In order to evaluate the performance of the proposed model, benchmark problems are used. At the authors' best knowledge, there are currently no benchmarks available in the literature considering energy in an FJSSP. Therefore, instances had to be created in order to test and validate this work. The choice was made to extend classical problems from the literature to support energy consumption. The chosen problems are taken from Brandimarte [46]. This consists of 10 problems (mk1 to mk10), where the jobs range from 10 to 20 operations, machines from 6 to 15, and operations for each job from 5 to 15. An energy consumption of every operation was added randomly, obeying a uniform distribution between 1 and 100. Thus, for each instance, the machining energy consumption and the idle power of machines are specified as inputs.

In this article, the unit of the makespan is unit of time and the unit of the energy consumption is in kWh.

5.1. Predictive Schedule Based on GA

Initially, the optimal scheduling scheme is acquired based on GA. Python programming is used to develop the proposed method using the distributed evolutionary algorithms in python framework (DEAP), which is a novel evolutionary computation framework. The parameters of GA are set as follows: the size of initial population is 50 and the number of generations is 500.

To validate the GA, a comparison with other methods in literature was made, such as PSO proposed by [47] and TS proposed by [48]. The result of the Brandimarte instances in terms of makespan of these different algorithms is presented in Table 3. The weight of the objective function of genetic algorithm is set to 1, to give importance to makespan rather than energy reduction.

Table 3. Results in terms of makespan (in time units) of the Brandimarte instances for different algorithms.

Instances	**The Proposed GA**	**PSO by [47]**	**TS by [48]**
Mk01	42	*41*	42
Mk02	32	*26*	32
Mk03	*206*	207	211
Mk04	67	*65*	81
Mk05	179	*171*	186
Mk06	86	*61*	86
Mk07	*164*	173	157
Mk08	*523*	*523*	*523*
Mk09	342	*307*	369
Mk10	*292*	312	296

Italics here identify the most effective algorithm through the lowest value of the makespan.

As can be seen from Table 3, the proposed GA gives similar results to PSO and TS algorithm when the weight is set to 1. Therefore, we consider this proposition as satisfying.

In the next step, more importance is given to energy reduction, therefore the weight of the objective function is modified. The Gantt chart of the predictive schedule using GA of Mk01 for different weight values is shown in Figure 3.

The makespan and energy consumption values for different cases are described in Table 4. This shows that the two objective functions are antagonistic. When the weight is set to 1, importance is given to makespan, therefore in this case GA provides the best makespan (42) but the biggest energy consumption value (2812). On the opposite, when the weight is set to 0, the importance is given to energy reduction, in this case GA provides the worst makespan (73) but the best energy consumption value (2229). It may be noted that when the weight decreases, makespan decreases but energy consumption increases.

5.2. Rescheduling Strategies

To illustrate the difference between the different rescheduling methods presented in Section 3.4, the predictive schedule of the instance MK01 where the weight is set to 1 is taken as example. A random perturbation (machine failure) is applied, assuming that at time $t = 20$, machine 1 is broken down and $t' = 6$ is the duration of the breakdown. The new schedules acquired by the three rescheduling methods (PR, TR and RSR) are presented in Figure 4, the red line representing the starting time and ending time of machine failure.

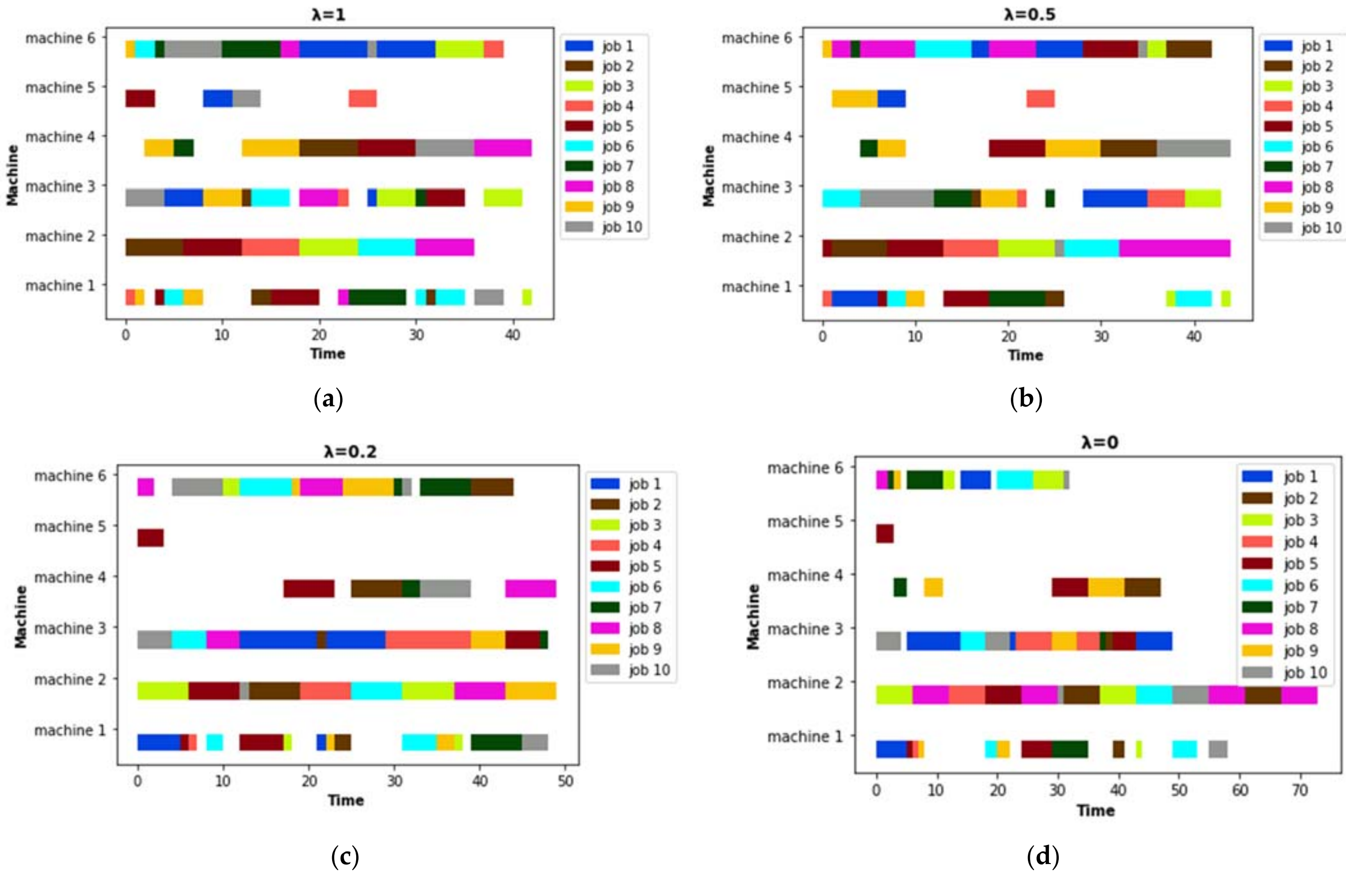
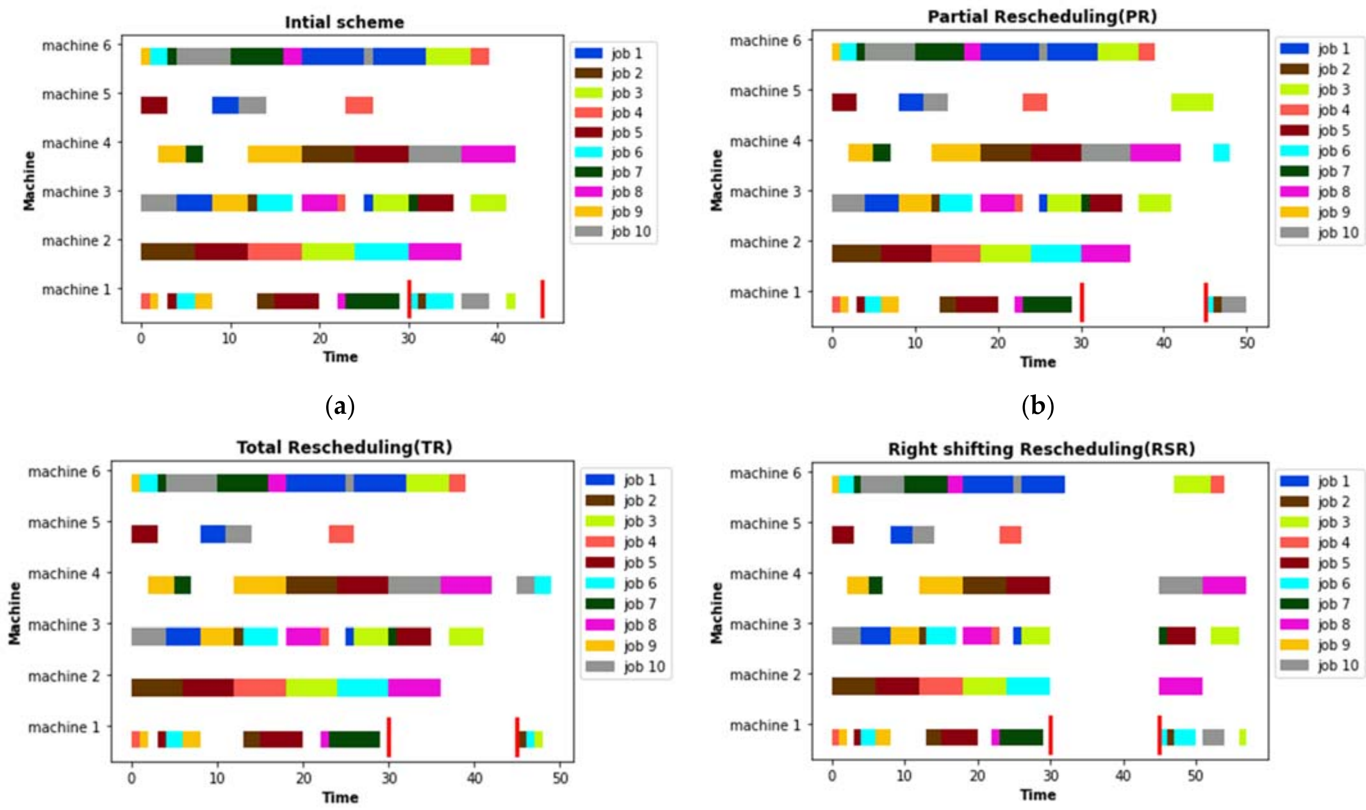


Figure 3. The predictive schedule for different weights of the objective functions. (**a**–**d**) represent respectively the predictive schedule when the weight of the objective function of GA algorithm is set to 1, 0.5, 0.2, or 0 respectively.

Table 4. Makespan (MK in time units) and energy consumption (EC in kWh) calculation example on MK01 instance.

Instance	Size	Weight	KPIs	
			MK	**EC**
MK01	10 × 6	1	42	2812
		0.5	44	2457
		0.2	49	2411
		0	73	2229

The directly affected operations by the failure machine are $O_{5,6}$, $O_{6,2}$, $O_{6,6}$, $O_{6,10}$, and $O_{6,3}$, these operations are executed by the broken-down machine. In PR, $O_{5,6}$, $O_{6,2}$, $O_{6,10}$ are postponed after the breakdown and the $O_{6,6}$ and $O_{6,3}$ are executed respectively on machine 4 and 5 with a different processing time (Figure 4b). In TR, all the remaining jobs are rescheduled using the GA algorithm after the breakdown (Figure 4c). As for RSR, all the remaining jobs are postponed by the breakdown duration (Figure 4d). The performance of the rescheduling methods is described in the Table 5.



(**a**) (**b**) (**c**) (**d**)

Figure 4. Demonstration of initial scheme, PR scheme, TR scheme and RSR scheme. (**a**) illustrates the predictive schedule, (**b**–**d**) illustrate the reactive schedule provided by the three rescheduling methods PR, TR and RSR respectively.

Table 5. The makespan (time units) and energy consumption (kWh) calculation for rescheduling methods on MK01 instance.

Schedule		**Makespan (MK)**	**Energy Consumption(EC)**
Predictive schedule		42	2812
Reactive schedule	PR schedule	50	3046
	TR schedule	49	2895
	RSR schedule	57	2887

As can be seen from Table 5, the three rescheduling methods gives different results. Both makespan and energy consumption are increased due to the presence of the machine failure that affects a set of operation. In terms of makespan, TR gives the best result (42), but in terms of energy consumption, RSR gives the best result (2887). This result can be explained by the date of the failure, which happened close to the end of the initial schedule.

5.3. Rescheduling Based on Q-Learning

To test the performance of the proposed Q-learning algorithm, we designed simulation experiments of machine failures. The parameters are set as follows:

- $\alpha = 1$: A learning rate of 1 means the old value will be completely discarded, the model converges quickly, no large number of episodes are required;
- $\gamma = 0$: The agent considers only immediate rewards. In each episode, one state is evaluated (the initial state of the system at a particular time, given the rescheduling time, the failure machine and the breakdown duration)

- $\varepsilon = 0.8$, the balance factor between exploration and exploitation. Exploration refers to searching over the whole sample space while exploitation refers to the exploitation of the promising areas found. In the proposed model, 80% is given to exploitation, so in 80% of cases the agent will choose the action with the biggest reward and in 20% of cases he will randomly choose an action to explore more of its environment.
- The number of episodes is 1000, for the model to converge.

In each episode the Q-table is updated depending on the value of the rewards (Figure 5).

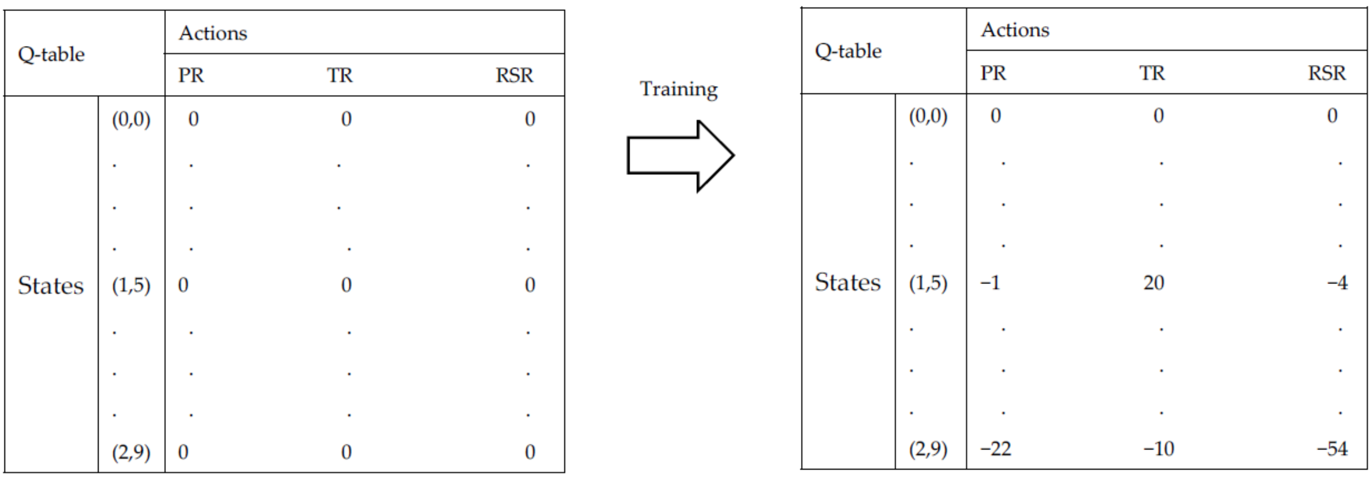


Figure 5. Q-table initialization and update.

5.3.1. The Single Objective Q-Learning

Two types of Q-learning algorithm are proposed in this article: the single objective Q-learning and multi-objective Q-learning.

The aim of the single objective function Q-learning is to minimize the makespan, which means the minimization of the delay time. The curve of the reward and the delay time in the first 50 episodes are described in Figure 6. It can be seen that the longer the delay time, the lower the reward value.

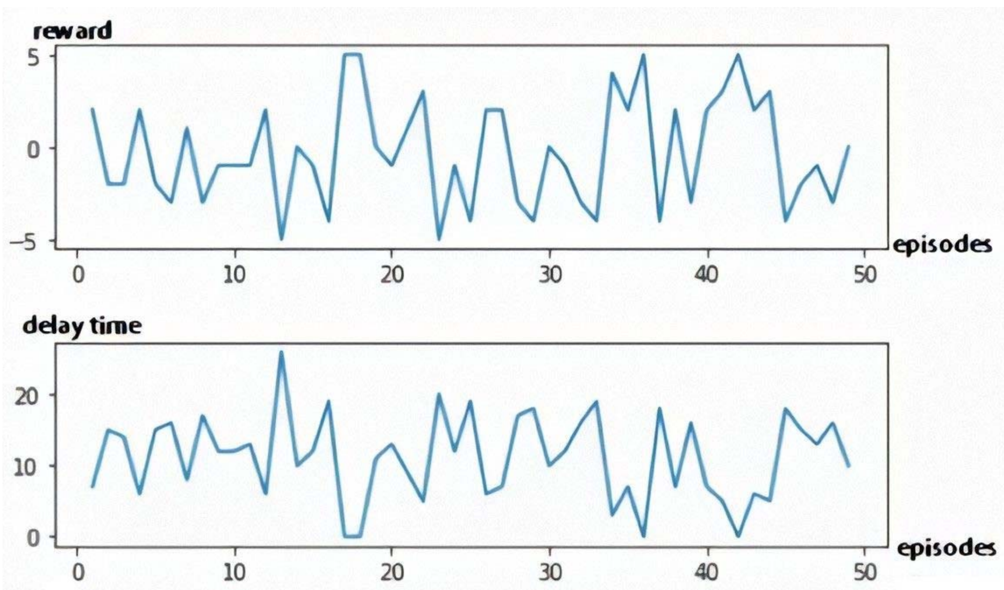


Figure 6. The evolution of reward value and delay time along episodes.

To show how the Q-values are updated in each episode, the state (0.7) is taken as example. Figure 7 describes the variation of Q-values of each action. The agent first selects the action 0 and gets a positive reward so its Q-value increases. After a few episodes, action 0 is chosen again because it has the biggest Q-value but gets a negative reward. Its Q-value thus decreases, giving the chance for action 1 to be selected. After that, action 1 is chosen in every episode because it gets a positive reward each time so its Q-value increases. Action 2 is selected in 100th and 800th episodes due to the ε-greedy where the agent still has a 20% probability to explore but its Q-value decreases because it gets negative rewards.

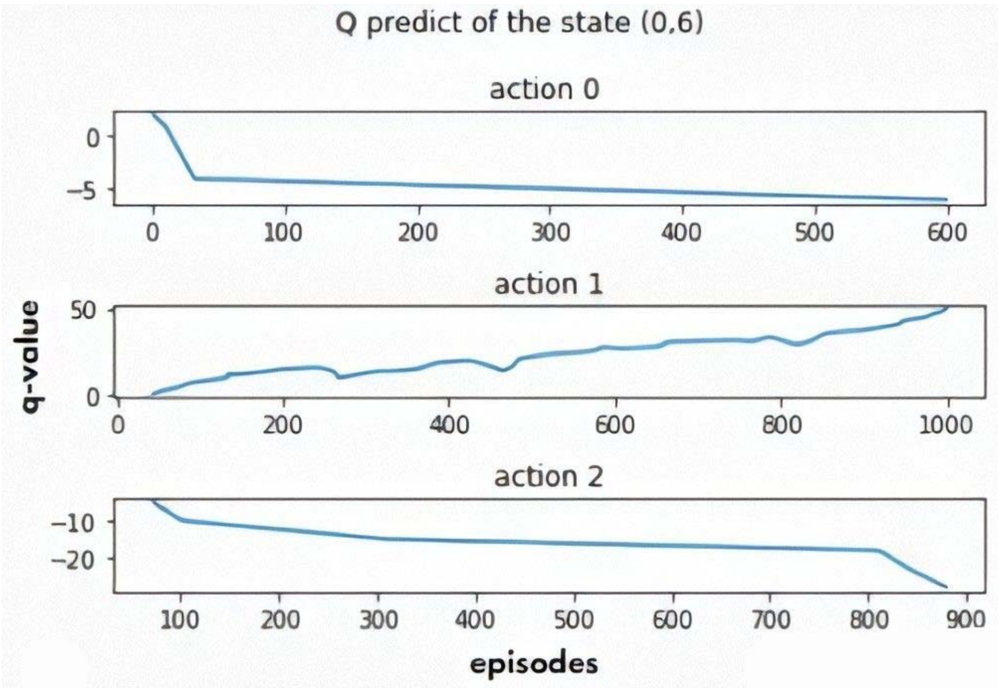


Figure 7. Q-value prediction of state (0.6).

5.3.2. The Multi-Objective Q-Learning

The goal of the multi-objective Q-learning approach is to minimize the makespan and the energy consumption at the same time. In this case, two rewards are considered: reward R_1 that depends on the delay time and reward R_2 that depends on the energy consumption deviation. Figure 8 describes the variation of the reward along the first 50 episodes. It can be seen that R_1 increases when the delay time decreases and R_2 increases when the energy consumption deviation decreases.

This time, state (1.9) is taken as an example and the weight of the objective function of the multi Q-learning algorithm is set to 0.5 (which means that makespan and energy consumption have the same importance). Throughout the episodes, action 1 gets positive rewards and its Q-value increases so it is selected most of the times, on the other hand action 0 and action 2 get negative rewards so their Q-values decrease, they are chosen only in the exploration phase. The Q-value prediction of the state (1.9) is presented in Figure 9.

5.4. Models Validation

The results of the optimal rescheduling methods for the Brandimarte [46] instances and the solution given by the Q-learning agent are represented in Appendix A. In Table 6, an extraction of Appendix A, corresponding to the instance MK01, is taken as example. The first column is the name of the instance, followed by its size and its level of flexibility. In the fourth column, the weight of the objective function of the GA and of the multi-objective Q-learning is defined. In the fifth column, makespan and energy consumption of the predictive schedule are calculated. In the sixth column, different types of machine failures are defined by their failure time, the reference of the failing machine and the failure duration. Next comes the state definition, then the rescheduling methods and their performance. In the last column the evaluated Q-learning approach is presented by giving the makespan (MK) and the energy consumption (EC) of the selected optimal rescheduling solution using single objective Q-learning and multi-objective Q-learning.

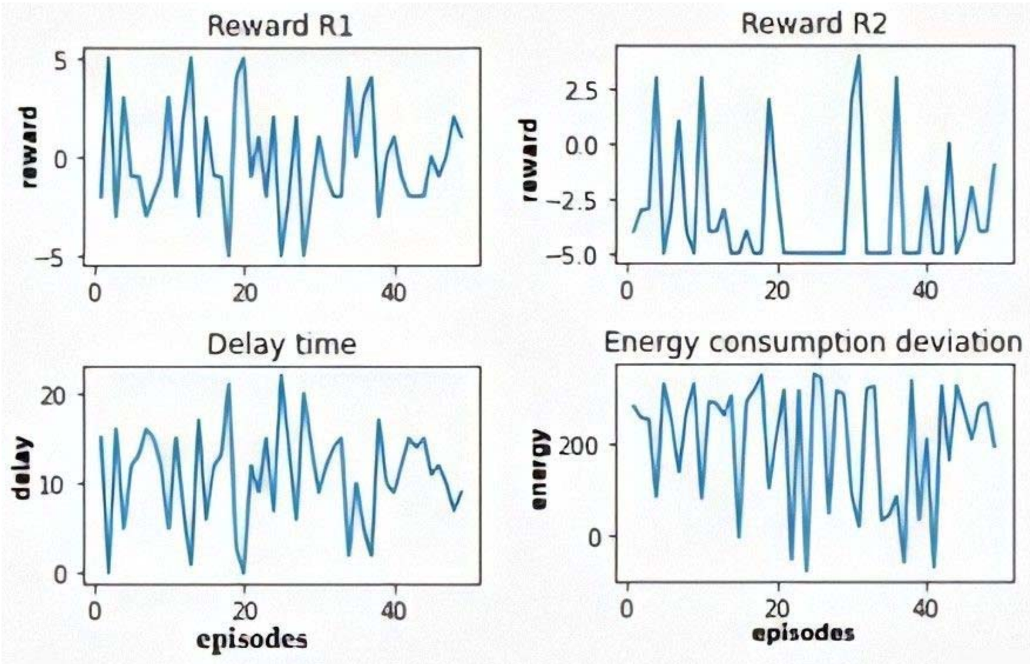


Figure 8. The change of rewards, delay time and energy consumption variation along episodes.

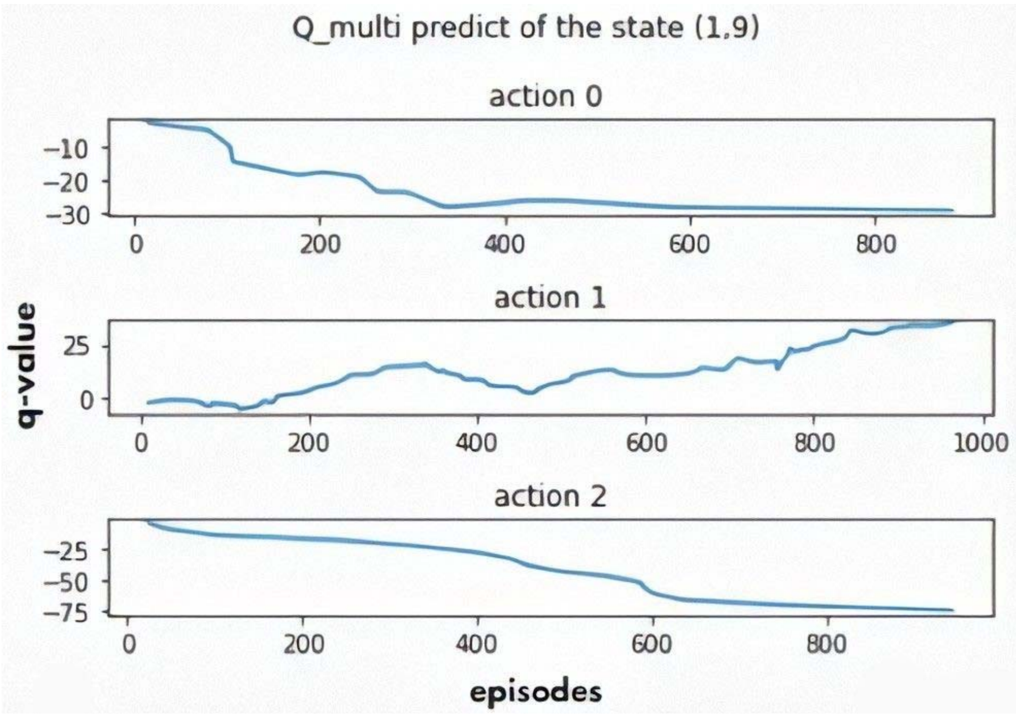


Figure 9. Q-value prediction of state (1.9).

Table 6. Performance measurement of the predictive and reactive schedule in MK01 instance.

Instance	Size	p	Weight of BF	Predictive Schedule		Machine Failure			State of the System	Reactive Schedule						Q-Learning	
										PR		TR		RSR			
				MK (Time Units)	EC (kWh)	Failure Time	Broken-Down Machine	Failure Duration		MK (Time Units)	EC (kWh)	MK (Time Units)	EC (kWh)	MK (Time Units)	EC (kWh)	Single Objective	Multi-Objective
MK01	10 × 6	2	1	42	3046	3	5	20	(0.5)	46	3064	45	3115	61	3160	TR	TR
						16	4	19	(1.9)	60	3128	55	3243	66	3180	TR	TR
						8	1	17	(0.6)	57	3099	50	3190	58	3142	TR	TR
						23	3	14	(1.7)	57	3101	56	3218	58	3142	TR	TR
						13	5	10	(0.4)	46	3058	45	3028	52	3106	TR	TR
						13	6	20	(0.9)	56	3098	54	3204	59	3148	TR	TR
			0.5	49	2837	11	1	12	(0.5)	54	2872	58	2826	61	2909	TR	TR
						7	5	23	(0.9)	56	2890	57	2724	76	2999	PR	TR
						22	2	22	(1.9)	62	2950	56	2968	65	2993	TR	TR
						5	2	12	(0.3)	54	2935	54	2853	55	2939	TR	TR
						11	1	12	(0.6)	54	2872	58	2826	61	2909	PR	PR
						13	4	13	(0.2)	50	2839	54	2816	54	2867	PR	PR
			0.2	52	2672	31	2	15	(1.9)	64	2702	67	2711	67	2672	PR	PR
						4	2	20	(0.4)	75	2797	78	2757	75	2800	TR	PR
						10	4	14	(0.0)	52	2673	58	2670	59	2714	PR	PR
						10	1	21	(0.6)	64	2728	68	2632	73	2798	TR	PR
						20	2	22	(1.7)	72	2769	76	2773	75	2820	PR	PR
						6	5	26	(0.9)	65	2727	68	2704	74	2804	PR	TR
			0	79	2554	23	6	20	(0.9)	91	2649	99	2612	102	2692	PR	TR
						1	5	26	(0.3)	79	2560	79	2574	102	2686	PR	PR
						31	2	37	(1.8)	92	2668	110	2706	116	2776	PR	PR
						3	2	24	(1.6)	88	2639	100	2666	106	2689	PR	PR
						16	2	34	(0.6)	98	2700	110	2744	116	2776	PR	PR
						30	6	20	(1.9)	79	2564	79	2605	98	2668	PR	PR

In the predictive schedule, when the weight decreases, the makespan increases but the energy consumption decreases. This is normal because importance is given to energy consumption each time the weight is decreased. After simulating different types of failure randomly, it can be seen that the Q-learning is able to choose the best rescheduling methods each time; the single objective Q-learning selects the best methods that minimize the makespan but the multi objective Q-learning selects the best methods that minimize the makespan and energy consumption depending on the value of the weight of the objective function.

When this weight is set to 1, the single objective and multi-objective Q-learning have the same results. They both choose the methods that minimize the makespan regardless of the value of the energy consumption. From Table 7, in the case of the MK01, TR proved to have the highest performance and was selected in both algorithms. Giving the same importance to energy consumption, which implies setting the value of the weight to 0.5, the selected method changes to make a compromise between the two objectives. There is a difference between the result of single objective and multi-objective Q-learning. Taking the state (0.9) as example, PR and TR gives 56 and 57 as makespan respectively and 2890 and 2724 as energy consumption respectively, so PR is selected by the single-objective Q-learning because it generates the minimum makespan, but TR is selected by the multi-objective Q-learning because it has better result than PR in terms of energy consumption.

Table 7. CPU time comparison.

Instances	CPU Time (s)	
	Traditional Rescheduling	**Q-Learning**
MK01	6.173	0.001
MK02	7.261	
MK03	45.068	
MK04	13.680	
MK05	24.488	
MK06	48.855	
MK07	30.716	
MK08	61.261	
MK09	85.610	
MK10	84.545	

By further decreasing the value of the weight to 0.2, more prominence is given to energy consumption. Taking the example of the state (0.4), PR and TR give 75 and 79 as makespan respectively and 2797 and 2757 as energy consumption respectively. Here PR is selected by the single objective Q-learning because it minimizes the makespan, but TR is selected by the multi-objective Q-learning because it has better optimization of the energy consumption that was given more importance. Once the weight is set to 0, the multi-objective Q-values selects the methods that optimizes the energy consumption regardless of the value of the makespan, as in state (0.9) when PR gave the best makespan (91) so it was selected by the single-objective Q-learning, but TR was selected by the multi-objective Q-learning because it gave the best energy consumption (2612).

Considering all the instances of the Brandimarte benchmark, in Appendix A, we can also deduce that the right shift rescheduling turned out to have the worst performance, this is due to the postponement of the remaining tasks which increases both the makespan and the energy variation. Another deduction that can be taken is that generally TR have the best performance in early failures and PR gives better results when the failures occur in the middle or in the end of the schedule and especially with instances that have high flexibility. The results of RSR also become improved at the end of the schedule because the number of postponed operations is smaller.

The Q-learning algorithm not only selects the optimal methods for rescheduling but also responds immediately to perturbation. Table 7 indicates the CPU time comparison between the time spent to execute the three rescheduling methods (PR, TR, RSR) and to select the optimal one and the time spent by the Q-learning algorithm to select the best method from the Q-table. The reported values are evaluated using a laptop computer with Intel core i5-8250U with 1.8 GHZ speed and with 12 Gb memory. The offline training of the Q-learning algorithm can take minutes or even some hours depending on the instance size, but it can be seen that, in online execution, the learning-based rescheduling selection of the optimal solution takes only one millisecond compared with traditional rescheduling that can exceed one minute, this time corresponds to state calculation of the system after perturbation and the selection of the best methods that have the highest Q-values from the corresponding Q-values table. However, the execution of the three rescheduling methods and the selection of the best method can take several seconds, even minutes when the instance is large.

6. Conclusions

This work deals with the flexible job shop scheduling problem under uncertainties. A multi-objective Q-learning rescheduling approach is proposed to solve the FJSSP under machine failures. Two key performance indicators are used to select the best schedule: the makespan and the energy consumption. The idea was not only to maintain effectiveness but also to improve energy efficiency. The approach is hybrid and combines predictive and reactive phases. The originality of this work is to combine AI and scheduling techniques to be able to rapidly solve a bi-objectives problem (makespan and energy consumption) of rescheduling in a context of FJSP.

First, a genetic algorithm was developed to provide an initial predictive schedule that minimizes the makespan and energy consumption simultaneously. In this predictive phase, different types of machine failures were simulated and classical rescheduling policies (RSR, TR, PR) were executed to repair the predictive scheduling and to find new solutions. Based on these results, the Q-learning agent is trained. To consider the energy consumption even in the rescheduling process, a multi-objective Q-learning algorithm was proposed. A weighting parameter is used to make a tradeoff between the makespan and the energy consumption. In the reactive phase, the Q-learning agent is tested on new machine disruptions. The Q-learning agent seeks to find the best action to take given the current state. In fact, the main goal of using AI tools is to be able to react quickly facing failures while rapidly selecting the best rescheduling policy related to the state of the environment. In order to assess the performance of the developed approach, the Brandimarte [46] benchmark was extended to support energy consumption. On this new benchmark, the Q-learning based rescheduling approach was tested to respond to unexpected machine failures and select the best rescheduling strategy.

The results of this study show that the approach proved to be effective in responding quickly and accurately to unexpected machine failures. The Q-learning algorithm provided appropriate strategy choices based on the state of the environment with various balance between the objectives of energy consumption and productivity. The learning phase was therefore efficient enough to enable these efficient choices. The choices of genetic algorithm and Q-learning algorithm proved their efficiency on the extended classical instances of Brandimarte in this work. Nevertheless, the approach leaves the possibility to the user to integrate their own choice of algorithm according to the specific context.

Future works are oriented to take into consideration other types of disruptions like new job insertions, variety of availability of energy, urgent job arrivals, etc. Another future perspective that can be expected is the evaluation of the proposed approach on other types of learning techniques in order to compare with the Q-learning algorithm. On a more global perspective, this work contributes to the development of efficient rescheduling approaches for the control of future industrial systems. Such systems are meant to integrate more and more flexibility, and the performance evaluation of this work on a FJSP shows the compatibility of the approach with this objective. This work also contributes to the integration of multi-objective rescheduling strategies in industry, which is especially relevant for sustainability concerns.

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Appendix A

Table A1. Performance evaluation of the Q-learning approach on the Brandimarte benchmark.

Instance	Size	p	Weight of BF	Predictive Schedule		Machine Failure			State of the System	Reactive Schedule						Q-Learning	
										PR		TR		RSR			
				MK (Time Units)	EC (kWh)	Failure Time	Broken-Down Machine	Failure Duration		MK (Time Units)	EC (kWh)	MK (Time Units)	EC (kWh)	MK (Time Units)	EC (kWh)	Single Objective	Multi-Objective
MK01	10 × 6	2	1	42	3046	3	5	20	(0.5)	46	3064	45	3115	61	3160	TR	TR
						16	4	19	(1.9)	60	3128	55	3243	66	3180	TR	TR
						8	1	17	(0.6)	57	3099	50	3190	58	3142	TR	TR
						23	3	14	(1.7)	57	3101	56	3218	58	3142	TR	TR
						13	5	10	(0.4)	46	3058	45	3028	52	3106	TR	TR
						13	6	20	(0.9)	56	3098	54	3204	59	3148	TR	TR
			0.5	49	2837	11	1	12	(0.5)	54	2872	58	2826	61	2909	TR	TR
						7	5	23	(0.9)	56	2890	57	2724	76	2999	PR	TR
						22	2	22	(1.9)	62	2950	56	2968	65	2993	TR	TR
						5	2	12	(0.3)	54	2935	54	2853	55	2939	TR	TR
						11	1	12	(0.6)	54	2872	58	2826	61	2909	PR	PR
						13	4	13	(0.2)	50	2839	54	2816	54	2867	PR	PR
			0.2	52	2672	31	2	15	(1.9)	64	2702	67	2711	67	2672	PR	PR
						4	2	20	(0.4)	75	2797	78	2757	75	2800	TR	PR
						10	4	14	(0.0)	52	2673	58	2670	59	2714	PR	PR
						10	1	21	(0.6)	64	2728	68	2632	73	2798	TR	PR
						20	2	22	(1.7)	72	2769	76	2773	75	2820	PR	PR
						6	5	26	(0.9)	65	2727	68	2704	74	2804	PR	TR
			0	79	2554	23	6	20	(0.9)	91	2649	99	2612	102	2692	PR	TR
						1	5	26	(0.3)	79	2560	79	2574	102	2686	PR	PR
						31	2	37	(1.8)	92	2668	110	2706	116	2776	PR	PR
						3	2	24	(1.6)	88	2639	100	2666	106	2689	PR	PR
						16	2	34	(0.6)	98	2700	110	2744	116	2776	PR	PR
						30	6	20	(1.9)	79	2564	79	2605	98	2668	PR	PR

Table A1. *Cont.*

Instance	Size	*p*	Weight of BF	Predictive Schedule		Machine Failure			State of the System	Reactive Schedule						Q-Learning	
										PR		TR		RSR			
				MK (Time Units)	EC (kWh)	Failure Time	Broken-Down Machine	Failure Duration		MK (Time Units)	EC (kWh)	MK (Time Units)	EC (kWh)	MK (Time Units)	EC (kWh)	Single Objective	Multi-Objective
MK02	10 × 6	3.5	1	32	3173	15	1	12	(1.7)	46	3234	45	3223	45	3263	TR	TR
						4	2	16	(0.7)	45	3216	47	3330	49	3263	PR	PR
						18	6	9	(1.8)	40	3205	37	3296	43	3239	TR	TR
						1	6	12	(0.3)	44	3223	46	3071	44	3245	PR	PR
						10	2	4	(0.9)	49	3232	52	3386	51	3287	PR	PR
						2	4	9	(0.4)	38	3191	37	3282	43	3239	TR	TR
			0.5	37	2479	5	6	17	(0.6)	49	2525	48	2334	56	2593	TR	TR
						17	6	11	(1.9)	42	2494	45	2334	50	2557	PR	TR
						25	6	13	(2.9)	45	2497	46	2384	50	2557	PR	TR
						10	1	9	(0.7)	44	2503	47	2187	46	2533	PR	TR
						18	6	9	(1.6)	42	2490	40	2342	46	2490	TR	TR
						5	4	11	(0.3)	38	2487	42	2288	50	2557	PR	TR
			0.2	49	1992	23	2	14	(1.7)	59	2035	62	2014	65	2088	PR	TR
						16	1	23	(0.9)	53	2018	54	1996	64	2082	PR	TR
						1	6	16	(0.4)	55	2017	50	1935	60	2058	TR	TR
						11	1	18	(0.7)	63	2014	52	1983	67	2100	TR	TR
						24	2	20	(1.9)	64	2062	57	2071	72	2130	PR	TR
						5	6	18	(0.6)	60	2040	58	1940	66	2040	TR	TR
			0	49	1964	21	4	16	(1.9)	56	1990	52	1996	66	2066	TR	PR
						35	3	20	(2.9)	66	2010	68	2045	71	2030	PR	PR
						2	4	15	(0.5)	55	2000	64	1990	65	2060	PR	TR
						10	4	19	(0.6)	61	2035	55	1992	69	2084	TR	TR
						10	5	20	(0.9)	60	2038	60	1985	68	2087	TR	TR
						22	1	14	(1.6)	52	1995	54	1981	64	2054	PR	PR

Table A1. *Cont.*

Instance	Size	p	Weight of BF	Predictive Schedule		Machine Failure			State of the System	Reactive Schedule						Q-Learning	
										PR		TR		RSR			
				MK (Time Units)	EC (kWh)	Failure Time	Broken-Down Machine	Failure Duration		MK (Time Units)	EC (kWh)	MK (Time Units)	EC (kWh)	MK (Time Units)	EC (kWh)	Single Objective	Multi-Objective
MK03	15 × 8	3	1	206	8846	113	4	70	(1.8)	255	9120	239	9135	279	9430	TR	TR
						45	6	66	(0.4)	254	9262	246	9042	272	9374	*TR*	TR
						55	2	59	(0.6)	250	9063	221	9263	268	9342	TR	TR
						75	2	53	(1.7)	250	9078	219	8824	272	9374	*TR*	TR
						1	2	65	(0.3)	221	9839	238	9001	246	9166	*PR*	PR
						57	8	82	(0.8)	269	9276	237	9160	301	9606	TR	TR
			0.5	227	7515	83	8	67	(1.8)	278	7787	254	7201	309	8171	TR	TR
						182	4	88	(2.9)	310	7905	296	7874	317	8235	*PR*	PR
						66	2	77	(0.6)	244	7618	249	7209	302	8115	*PR*	TR
						44	1	80	(0.4)	304	8014	307	7516	317	8235	*PR*	TR
						94	4	66	(1.4)	266	7791	242	7387	297	8075	*PR*	PR
						97	3	67	(1.4)	264	7969	243	7426	276	7907	*PR*	PR
			0.2	231	7200	94	2	98	(1.9)	273	7408	263	7275	335	8032	*TR*	TR
						29	4	76	(0.5)	284	7598	291	7222	300	7832	*PR*	TR
						13	1	111	(0.6)	355	8042	368	8118	355	8192	*PR*	PR
						98	3	116	(1.8)	337	7907	278	7327	349	8136	*TR*	TR
						170	4	88	(2.9)	304	7544	282	7497	313	7856	*TR*	TR
						40	1	116	(0.7)	334	7958	350	7742	353	8176	*PR*	TR
			0	253	6574	152	6	97	(1.9)	328	7040	336	6952	348	7239	*PR*	TR
						64	4	67	(0.4)	282	6790	325	6900	325	7150	*PR*	PR
						105	1	103	(1.8)	341	7081	338	7080	369	7502	*TR*	TR
						43	8	121	(0.7)	296	7010	276	6816	358	7414	*TR*	TR
						30	8	104	(0.6)	278	6983	299	6916	361	7438	*PR*	TR
						86	3	73	(1.5)	297	6846	288	6805	334	7222	*PR*	TR

Table A1. *Cont.*

Instance	Size	p	Weight of BF	Predictive Schedule		Machine Failure			State of the System	Reactive Schedule						Q-Learning	
										PR		TR		RSR			
				MK (Time Units)	EC (kWh)	Failure Time	Broken-Down Machine	Failure Duration		MK (Time Units)	EC (kWh)	MK (Time Units)	EC (kWh)	MK (Time Units)	EC (kWh)	Single Objective	Multi-Objective
MK04	15 × 8	2	1	67	5206	6	4	31	(0.6)	102	5427	84	5214	102	5486	TR	TR
						1	3	17	(0.1)	74	5249	77	5398	84	5334	PR	PR
						49	3	27	(2.9)	110	5398	94	5347	109	5470	TR	TR
						30	2	17	(1.3)	67	5206	72	5315	84	5342	PR	PR
						11	2	19	(0.3)	67	5206	75	5342	87	5366	PR	PR
						1	7	26	(0.4)	83	5324	87	5495	93	5422	PR	PR
			0.5	73	4872	43	3	26	(1.9)	96	4976	87	4891	99	5080	TR	TR
						34	4	25	(1.7)	71	4999	68	5054	98	5072	TR	TR
						3	1	23	(0.4)	95	5015	93	5023	99	5080	TR	TR
						28	6	18	(1.8)	98	5007	84	4976	95	5048	TR	TR
						3	6	20	(0.3)	84	4974	85	4723	94	5040	PR	TR
						36	2	28	(1.4)	73	4886	78	4930	80	4886	PR	PR
			0.2	76	4562	40	4	35	(1.9)	106	4738	92	4724	112	4850	TR	TR
						7	1	27	(0.4)	103	4779	107	4723	104	4786	PR	TR
						42	7	21	(1.7)	95	4635	88	5479	101	4579	PR	TR
						21	3	30	(0.7)	109	4750	90	4615	109	4826	PR	TR
						30	1	37	(1.8)	110	4742	105	4810	113	4858	TR	PR
						11	6	25	(0.5)	87	4621	85	4600	103	4778	PR	TR
			0	90	4406	37	4	32	(1.7)	107	4510	102	4572	126	4658	TR	PR
						23	2	41	(0.7)	94	4459	96	4462	131	4734	PR	PR
						33	3	39	(1.9)	113	4528	107	4559	129	4679	TR	PR
						8	7	36	(0.5)	135	4611	121	4580	130	4726	TR	TR
						3	5	28	(0.8)	96	4492	105	4488	121	4654	PR	TR
						20	7	24	(0.4)	108	4490	103	4518	114	4598	TR	PR

Table A1. *Cont.*

Instance	Size	p	Weight of BF	Predictive Schedule		Machine Failure			State of the System	Reactive Schedule						Q-Learning	
										PR		TR		RSR			
				MK (Time Units)	EC (kWh)	Failure Time	Broken-Down Machine	Failure Duration		MK (Time Units)	EC (kWh)	MK (Time Units)	EC (kWh)	MK (Time Units)	EC (kWh)	Single Objective	Multi-Objective
MK05	15 × 4	1.5	1	179	5577	30	2	81	(0.5)	260	5866	227	6121	286	5925	TR	TR
						116	3	50	(1.9)	224	5702	225	5676	230	5781	PR	PR
						84	2	48	(1.5)	229	5741	206	5777	229	5777	TR	TR
						124	4	48	(2.8)	229	5749	216	5639	230	5781	TR	TR
						28	3	48	(0.3)	234	5766	210	5496	234	5797	TR	TR
						5	3	78	(0.4)	257	5855	234	5911	257	5889	TR	TR
			0.5	186	4977	134	1	79	(2.9)	257	5243	231	5248	262	5309	TR	TR
						57	3	67	(0.5)	256	5197	247	5177	256	5257	PR	PR
						77	2	86	(1.8)	262	5227	234	5162	273	5325	TR	TR
						49	3	87	(0.6)	276	5277	252	5384	276	5337	TR	TR
						122	4	65	(1.9)	246	5202	240	5216	255	5253	TR	TR
						13	4	64	(0.4)	257	5247	223	5120	257	5261	TR	TR
			0.2	197	4834	89	2	51	(1.5)	241	4990	216	4882	252	5054	TR	TR
						2	3	55	(0.3)	256	5030	232	4956	254	5062	TR	TR
						43	2	71	(0.5)	261	5058	212	4925	274	5142	TR	TR
						159	4	80	(2.9)	280	5156	274	5112	280	5166	TR	TR
						15	2	62	(1.8)	243	4982	218	4888	260	5086	TR	TR
						105	4	57	(1.6)	247	5027	243	4958	255	5066	TR	TR
			0	223	4751	171	4	92	(2.9)	311	5015	294	5050	311	5103	TR	TR
						15	3	58	(0.3)	284	4980	286	5049	289	5007	PR	RR
						19	1	77	(0.5)	257	4901	247	4911	299	5055	TR	PR
						93	3	66	(1.5)	287	4998	270	4950	295	5039	TR	TR
						111	4	68	(1.7)	287	5002	268	4922	291	5023	TR	TR
						140	2	104	(1.9)	281	5002	284	4990	284	5139	PR	TR

Table A1. *Cont.*

Instance	Size	*p*	Weight of BF	Predictive Schedule		Machine Failure			State of the System	Reactive Schedule						Q-Learning	
										PR		TR		RSR			
				MK (Time Units)	EC (kWh)	Failure Time	Broken-Down Machine	Failure Duration		MK (Time Units)	EC (kWh)	MK (Time Units)	EC (kWh)	MK (Time Units)	EC (kWh)	Single Objective	Multi-Objective
MK06	10 × 15	3	1	86	8108	6	7	30	(0.5)	116	8359	114	8646	121	8458	TR	TR
						57	7	33	(1.9)	116	8317	107	8317	119	8438	TR	TR
						25	8	25	(0.3)	106	8235	107	8317	114	8388	PR	PR
						37	8	26	(1.7)	104	8202	95	8563	107	8318	TR	TR
						18	8	43	(0.7)	143	8471	115	8597	130	8548	TR	TR
						35	6	43	(1.6)	106	8242	99	8421	118	8428	TR	TR
			0.5	99	8004	57	5	33	(1.8)	127	8156	117	8039	135	8364	TR	TR
						25	7	47	(0.7)	143	8359	141	7669	147	8484	TR	TR
						3	6	41	(0.3)	131	8193	121	7749	141	8424	TR	TR
						54	2	49	(1.9)	135	8885	120	7800	140	8414	TR	TR
						83	1	46	(2.9)	142	8212	139	8164	145	8346	TR	TR
						29	4	50	(0.8)	130	8265	133	7728	153	8534	PR	TR
			0.2	114	7435	1	8	51	(1.8)	143	7630	138	7254	162	7915	TR	TR
						6	7	31	(0.3)	147	7748	149	7140	150	7795	PR	TR
						91	5	32	(1.9)	161	7843	153	7438	171	8005	TR	TR
						78	8	34	(2.9)	131	7547	128	7370	150	7795	TR	TR
						34	9	35	(0.5)	121	7528	134	7071	145	7725	PR	TR
						26	9	51	(0.7)	239	7658	239	7459	164	7935	PR	TR
			0	141	6564	26	9	64	(0.6)	148	6807	163	6885	206	7214	PR	PR
						66	5	51	(1.8)	150	6716	159	6746	186	7014	PR	PR
						36	1	60	(0.7)	172	6930	181	6875	202	7147	PR	TR
						94	7	39	(2.9)	167	6702	162	6753	185	6916	TR	PR
						30	2	61	(0.9)	159	6881	160	6700	196	7114	PR	TR
						49	9	44	(1.7)	155	6822	158	6643	184	6994	PR	TR

Table A1. *Cont.*

Instance	Size	*p*	Weight of BF	Predictive Schedule		Machine Failure			State of the System	Reactive Schedule						Q-Learning	
										PR		TR		RSR			
				MK (Time Units)	EC (kWh)	Failure Time	Broken-Down Machine	Failure Duration		MK (Time Units)	EC (kWh)	MK (Time Units)	EC (kWh)	MK (Time Units)	EC (kWh)	Single Objective	Multi-Objective
MK07	20 × 5	3	1	164	5599	43	1	59	(0.5)	220	5803	200	5702	226	5909	PR	TR
						112	5	77	(2.9)	242	5891	221	5841	244	5999	TR	TR
						8	5	73	(0.4)	228	5861	208	5834	237	5964	TR	TR
						65	2	75	(1.8)	217	5872	196	5656	240	5979	TR	TR
						52	4	75	(0.7)	244	5942	245	5875	244	5999	PR	PR
						1	5	58	(0.3)	214	5495	222	5633	223	5894	PR	PR
			0.5	189	4699	5	1	86	(0.5)	270	4920	228	4695	280	5154	TR	TR
						86	4	84	(1.9)	274	4950	248	4932	274	5124	TR	TR
						77	2	54	(1.5)	243	4982	206	4624	258	5044	TR	TR
						59	1	84	(0.7)	243	4899	234	4569	273	5119	TR	TR
						145	1	89	(2.9)	272	4859	254	4964	285	5179	TR	TR
						94	1	48	(1.7)	233	4799	208	4564	248	4994	TR	TR
			0.2	220	4345	81	5	62	(1.5)	285	4577	248	4277	290	4695	TR	TR
						157	1	94	(2.9)	288	4493	275	4553	317	4830	TR	TR
						39	3	92	(0.5)	307	4750	273	4267	312	4805	TR	TR
						87	2	78	(1.7)	253	4518	257	4366	299	4740	PR	TR
						35	2	102	(0.8)	276	4658	294	4498	339	4890	PR	TR
						110	4	80	(1.8)	299	4696	288	4563	300	4745	TR	TR
			0	236	4097	44	2	61	(0.7)	253	4216	272	4092	297	4407	PR	TR
						79	3	111	(1.9)	285	4381	290	4290	350	4667	PR	TR
						51	3	99	(0.9)	267	4319	271	4198	332	4577	PR	TR
						55	4	77	(0.5)	297	4355	310	4228	326	4547	PR	TR
						172	4	104	(2.9)	316	4298	325	4452	341	4517	PR	PR
						99	1	72	(1.5)	302	4331	269	4178	308	4457	TR	TR

Table A1. *Cont.*

Instance	Size	*p*	Weight of BF	Predictive Schedule		Machine Failure			State of the System	Reactive Schedule						Q-Learning	
										PR		TR		RSR			
				MK (Time Units)	EC (kWh)	Failure Time	Broken-Down Machine	Failure Duration		MK (Time Units)	EC (kWh)	MK (Time Units)	EC (kWh)	MK (Time Units)	EC (kWh)	Single Objective	Multi-Objective
MK08	20 × 10	1.5	1	523	13,255	292	7	250	(1.9)	613	13,956	604	14,405	775	15,523	PR	PR
						125	7	192	(0.7)	579	13,683	582	13,250	715	14,983	PR	PR
						94	1	153	(0.3)	681	14,735	693	14,974	681	14,677	PR	PR
						242	3	185	(1.8)	584	13,809	577	13,755	701	14,938	TR	TR
						86	9	207	(0.5)	559	13,579	567	13,712	727	15,091	PR	PR
						238	3	151	(1.7)	568	13,684	555	13,458	672	14,596	TR	TR
			0.5	524	12,499	81	5	258	(0.8)	495	13,852	401	13,451	487	14,596	TR	TR
						216	2	189	(1.9)	292	12,902	293	12,979	372	13,642	PR	PR
						106	9	139	(0.5)	280	12,699	273	12,587	371	13,552	TR	TR
						10	7	227	(0.6)	434	14,046	340	13,581	491	14,632	TR	TR
						418	10	152	(2.9)	404	13,048	393	13,226	420	13,495	TR	TR
						42	3	196	(0.4)	359	13,481	330	13,013	458	14,335	TR	TR
			0.2	543	12,365	337	7	159	(1.9)	619	12,848	595	12,872	682	13,616	TR	TR
						132	5	226	(0.8)	646	13,377	632	13,348	773	14,435	TR	TR
						201	8	174	(1.6)	631	13,198	589	12,976	720	13,958	TR	TR
						131	1	184	(0.4)	717	14,009	734	13,683	728	14,030	PR	TR
						320	1	158	(1.8)	689	13,467	699	13,173	709	13,859	PR	TR
						15	3	147	(0.3)	592	12,889	581	12,550	690	13,688	TR	TR
			0	561	12,320	194	9	260	(1.9)	590	12,810	584	12,949	785	14,336	TR	PR
						29	10	146	(0.3)	750	13,720	714	13,661	722	13,769	TR	TR
						126	4	260	(0.9)	607	13,062	612	12,789	821	14,660	PR	TR
						214	10	140	(1.4)	694	13,464	667	13,404	703	13,598	TR	TR
						430	10	204	(2.9)	782	13,396	744	13,420	782	13,876	TR	PR
						86	3	263	(0.8)	689	13,809	640	13,244	826	14,687	TR	TR

Table A1. *Cont.*

Instance	Size	p	Weight of BF	Predictive Schedule		Machine Failure			State of the System	Reactive Schedule						Q-Learning	
										PR		TR		RSR			
				MK (Time Units)	EC (kWh)	Failure Time	Broken-Down Machine	Failure Duration		MK (Time Units)	EC (kWh)	MK (Time Units)	EC (kWh)	MK (Time Units)	EC (kWh)	Single Objective	Multi-Objective
MK09	20 × 10	3	1	342	13,900	189	2	132	(1.8)	464	14,965	413	14,429	567	15,250	TR	TR
						244	7	97	(2.9)	518	14,433	488	14,404	531	14,890	TR	TR
						68	10	107	(0.2)	372	14,124	382	14,259	441	14,890	PR	PR
						50	9	94	(0.4)	377	14,259	379	14,044	424	14,720	PR	PR
						115	1	97	(1.5)	413	14,533	478	14,341	423	14,810	PR	PR
						112	9	91	(0.5)	467	14,212	451	14,176	442	14,900	TR	TR
			0.5	362	12,788	215	4	144	(1.9)	504	13,813	438	13,166	507	14,238	TR	TR
						115	6	90	(0.4)	369	12,841	382	12,566	445	13,518	PR	TR
						141	6	91	(1.6)	369	12,884	373	12,642	462	13,788	PR	TR
						261	2	102	(2.9)	443	13,637	442	13,389	442	13,798	TR	TR
						122	5	175	(1.7)	458	13,583	452	13,434	529	14,458	TR	TR
						29	10	181	(0.6)	726	13,635	693	12,213	815	14,618	TR	TR
			0.2	367	12,437	228	8	134	(1.9)	501	13,260	483	13,236	506	13,827	TR	TR
						34	10	97	(0.2)	378	12,529	393	12,566	448	13,247	PR	PR
						43	9	169	(0.7)	455	13,258	486	13,009	538	14,147	PR	TR
						184	6	93	(1.5)	405	12,760	412	12,314	452	13,287	PR	TR
						245	8	177	(2.9)	537	13,469	514	13,413	549	14,257	TR	TR
						92	9	142	(0.6)	441	13,012	435	12,495	510	13,867	TR	TR
			0	434	12,322	118	8	126	(0.4)	548	13,358	528	13,451	562	13,062	TR	TR
						187	10	192	(1.7)	520	13,031	457	12,622	628	14,262	TR	TR
						46	2	185	(0.6)	514	13,154	491	13,579	612	14,102	TR	TR
						186	1	193	(1.8)	555	13,585	541	13,309	627	14,252	TR	TR
						13	1	215	(0.5)	569	13,729	563	14,034	651	14,492	TR	TR
						244	1	158	(1.9)	532	13,330	527	13,199	588	13,862	TR	TR

Table A1. *Cont.*

Instance	Size	*p*	Weight of BF	Predictive Schedule		Machine Failure			State of the System	Reactive Schedule						Q-Learning	
										PR		TR		RSR			
				MK (Time Units)	EC (kWh)	Failure Time	Broken-Down Machine	Failure Duration		MK (Time Units)	EC (kWh)	MK (Time Units)	EC (kWh)	MK (Time Units)	EC (kWh)	Single Objective	Multi-Objective
MK10	20 × 15	1.5	1	292	13,707	1	8	148	(1.8)	365	14,400	356	14,376	421	15,126	TR	TR
						57	9	79	(0.4)	342	14,155	330	13,920	367	14,631	TR	TR
						88	9	132	(0.7)	396	14,630	367	14,336	531	15,236	TR	TR
						203	1	130	(2.9)	415	14,436	366	14,331	429	15,214	TR	TR
						41	1	86	(0.3)	345	14,050	326	14,246	379	14,664	TR	TR
						119	4	139	(1.7)	363	14,400	345	14,095	419	15,104	TR	TR
			0.5	297	12,710	10	7	146	(0.5)	420	13,946	409	13,082	453	14,426	TR	TR
						212	2	135	(2.9)	319	13,494	393	13,629	436	14,239	TR	TR
						122	6	86	(1.7)	370	13,235	322	12,722	390	13,733	TR	TR
						17	13	128	(0.4)	307	12,787	311	12,340	359	13,392	PR	TR
						157	4	138	(1.9)	391	13,667	368	12,983	444	14,327	TR	TR
						91	3	125	(0.7)	372	13,327	359	12,538	414	13,997	TR	TR
			0.2	316	11,826	8	3	150	(0.4)	352	12,223	385	12,334	474	13,564	PR	PR
						125	8	83	(1.6)	354	12,252	350	11,921	406	12,816	TR	TR
						123	7	156	(1.9)	410	12,802	401	12,610	484	13,674	TR	TR
						50	6	150	(0.6)	403	12,705	400	12,049	469	13,509	TR	TR
						151	5	123	(1.8)	427	12,852	388	12,249	450	13,300	PR	PR
						254	3	156	(2.9)	457	12,516	438	12,582	463	13,296	TR	PR
			0	344	11,483	54	10	91	(0.7)	375	11,848	370	11,747	438	12,517	TR	TR
						72	8	126	(0.5)	405	12,117	440	11,758	473	12,902	PR	TR
						162	1	102	(1.6)	410	11,999	378	11,732	451	12,553	PR	TR
						272	7	136	(2.9)	451	11,838	435	12,241	485	12,750	TR	PR
						112	8	143	(0.8)	436	12,441	422	12,176	494	13,133	TR	TR
						178	4	169	(1.9)	438	12,381	429	12,135	514	13,183	TR	TR

References

1. Giret, A.; Trentesaux, D.; Prabhu, V. Sustainability in Manufacturing Operations Scheduling: A State of the Art Review. *J. Manuf. Syst.* **2015**, *37*, 126–140. [CrossRef]
2. Zhang, L.; Li, X.; Gao, L.; Zhang, G. Dynamic Rescheduling in FMS That Is Simultaneously Considering Energy Consumption and Schedule Efficiency. *Int. J. Adv. Manuf. Technol.* **2016**, *87*, 1387–1399. [CrossRef]
3. Nouiri, M.; Bekrar, A.; Trentesaux, D. Towards Energy Efficient Scheduling and Rescheduling for Dynamic Flexible Job Shop Problem. *IFAC-Pap.* **2018**, *51*, 1275–1280. [CrossRef]
4. Masmoudi, O.; Delorme, X.; Gianessi, P. Job-Shop Scheduling Problem with Energy Consideration. *Int. J. Prod. Econ.* **2019**, *216*, 12–22. [CrossRef]
5. Liu, Y.; Dong, H.; Lohse, N.; Petrovic, S. A Multi-Objective Genetic Algorithm for Optimisation of Energy Consumption and Shop Floor Production Performance. *Int. J. Prod. Econ.* **2016**, *179*, 259–272. [CrossRef]
6. Kemmoe, S.; Lamy, D.; Tchernev, N. Job-Shop like Manufacturing System with Variable Power Threshold and Operations with Power Requirements. *Int. J. Prod. Res.* **2017**, *55*, 6011–6032. [CrossRef]
7. Raileanu, S.; Anton, F.; Iatan, A.; Borangiu, T.; Anton, S.; Morariu, O. Resource Scheduling Based on Energy Consumption for Sustainable Manufacturing. *J. Intell. Manuf.* **2017**, *28*, 1519–1530. [CrossRef]
8. Mokhtari, H.; Hasani, A. An Energy-Efficient Multi-Objective Optimization for Flexible Job-Shop Scheduling Problem. *Comput. Chem. Eng.* **2017**, *104*, 339–352. [CrossRef]
9. Gong, X.; De Pessemier, T.; Martens, L.; Joseph, W. Energy-and Labor-Aware Flexible Job Shop Scheduling under Dynamic Electricity Pricing: A Many-Objective Optimization Investigation. *J. Clean. Prod.* **2019**, *209*, 1078–1094. [CrossRef]
10. Chen, X.; Li, J.; Han, Y.; Sang, H. Improved Artificial Immune Algorithm for the Flexible Job Shop Problem with Transportation Time. *Meas. Control* **2020**, *53*, 2111–2128. [CrossRef]
11. Salido, M.A.; Escamilla, J.; Barber, F.; Giret, A. Rescheduling in Job-Shop Problems for Sustainable Manufacturing Systems. *J. Clean. Prod.* **2017**, *162*, S121–S132. [CrossRef]
12. Caldeira, R.H.; Gnanavelbabu, A.; Vaidyanathan, T. An Effective Backtracking Search Algorithm for Multi-Objective Flexible Job Shop Scheduling Considering New Job Arrivals and Energy Consumption. *Comput. Ind. Eng.* **2020**, *149*, 106863. [CrossRef]
13. Xu, B.; Mei, Y.; Wang, Y.; Ji, Z.; Zhang, M. Genetic Programming with Delayed Routing for Multiobjective Dynamic Flexible Job Shop Scheduling. *Evol. Comput.* **2021**, *29*, 75–105. [CrossRef]
14. Luo, J.; El Baz, D.; Xue, R.; Hu, J. Solving the Dynamic Energy Aware Job Shop Scheduling Problem with the Heterogeneous Parallel Genetic Algorithm. *Future Gener. Comput. Syst.* **2020**, *108*, 119–134. [CrossRef]
15. Tian, S.; Wang, T.; Zhang, L.; Wu, X. An Energy-Efficient Scheduling Approach for Flexible Job Shop Problem in an Internet of Manufacturing Things Environment. *IEEE Access* **2019**, *7*, 62695–62704. [CrossRef]
16. Nouiri, M.; Trentesaux, D.; Bekrar, A. EasySched: Une Architecture Multi-Agent Pour l'ordonnancement Prédictif et Réactif de Systèmes de Production de Biens En Fonction de l'énergie Renouvelable Disponible Dans Un Contexte Industrie 4.0. *arXiv* **2019**, arXiv:1905.12083. [CrossRef]
17. Bishop, C.M. *Pattern Recognition and Machine Learning (Information Science and Statistics)*; Springer: Berlin, Germany, 2007.
18. Shahzad, A.; Mebarki, N. Learning Dispatching Rules for Scheduling: A Synergistic View Comprising Decision Trees, Tabu Search and Simulation. *Computers* **2016**, *5*, 3. [CrossRef]
19. Wang, C.L.; Rong, G.; Weng, W.; Feng, Y.P. Mining Scheduling Knowledge for Job Shop Scheduling Problem. *IFAC-Pap.* **2015**, *48*, 800–805. [CrossRef]
20. Zhao, M.; Gao, L.; Li, X. A Random Forest-Based Job Shop Rescheduling Decision Model with Machine Failures. *J. Ambient. Intell. Humaniz. Comput.* **2019**, 1–11. [CrossRef]
21. Li, Y.; Carabelli, S.; Fadda, E.; Manerba, D.; Tadei, R.; Terzo, O. Machine Learning and Optimization for Production Rescheduling in Industry 4.0. *Int. J. Adv. Manuf. Technol.* **2020**, *110*, 2445–2463. [CrossRef]
22. Pereira, M.S.; Lima, F. A Machine Learning Approach Applied to Energy Prediction in Job Shop Environments. In Proceedings of the IECON 2018-44th Annual Conference of the IEEE Industrial Electronics Society, Washington, DC, USA, 21–23 October 2018; pp. 2665–2670.
23. Li, Y.; Chen, Y. Neural Network and Genetic Algorithm-Based Hybrid Approach to Dynamic Job Shop Scheduling Problem. In Proceedings of the 2009 IEEE International Conference on Systems, Man and Cybernetics, San Antonio, TX, USA, 11–14 October 2009; pp. 4836–4841.
24. Wang, C.; Jiang, P. Manifold Learning Based Rescheduling Decision Mechanism for Recessive Disturbances in RFID-Driven Job Shops. *J. Intell. Manuf.* **2018**, *29*, 1485–1500. [CrossRef]
25. Mihoubi, B.; Bouzouia, B.; Gaham, M. Reactive Scheduling Approach for Solving a Realistic Flexible Job Shop Scheduling Problem. *Int. J. Prod. Res.* **2021**, *59*, 5790–5808. [CrossRef]
26. Adibi, M.A.; Shahrabi, J. A Clustering-Based Modified Variable Neighborhood Search Algorithm for a Dynamic Job Shop Scheduling Problem. *Int. J. Adv. Manuf. Technol.* **2014**, *70*, 1955–1961. [CrossRef]
27. Sutton, R.S.; Barto, A.G. *Reinforcement Learning: An Introduction*; MIT Press: Cambridge, MA, USA, 2018.

28. Riedmiller, S.; Riedmiller, M. A Neural Reinforcement Learning Approach to Learn Local Dispatching Policies in Production Scheduling. In Proceedings of the IJCAI, Stockholm, Sweden, 31 July–6 August 1999; Volume 2, pp. 764–771.
29. Chen, X.; Hao, X.; Lin, H.W.; Murata, T. Rule Driven Multi Objective Dynamic Scheduling by Data Envelopment Analysis and Reinforcement Learning. In Proceedings of the 2010 IEEE International Conference on Automation and Logistics, Hong Kong and Macau, China, 16–20 August 2010; pp. 396–401.
30. Gabel, T.; Riedmiller, M. Distributed Policy Search Reinforcement Learning for Job-Shop Scheduling Tasks. *Int. J. Prod. Res.* **2012**, *50*, 41–61. [CrossRef]
31. Zhao, M.; Li, X.; Gao, L.; Wang, L.; Xiao, M. An Improved Q-Learning Based Rescheduling Method for Flexible Job-Shops with Machine Failures. In Proceedings of the 2019 IEEE 15th International Conference on Automation Science and Engineering (CASE), Vancouver, BC, Canada, 22–26 August 2019; pp. 331–337.
32. Shahrabi, J.; Adibi, M.A.; Mahootchi, M. A Reinforcement Learning Approach to Parameter Estimation in Dynamic Job Shop Scheduling. *Comput. Ind. Eng.* **2017**, *110*, 75–82. [CrossRef]
33. Luo, S. Dynamic Scheduling for Flexible Job Shop with New Job Insertions by Deep Reinforcement Learning. *Appl. Soft Comput.* **2020**, *91*, 106208. [CrossRef]
34. Bouazza, W.; Sallez, Y.; Beldjilali, B. A Distributed Approach Solving Partially Flexible Job-Shop Scheduling Problem with a Q-Learning Effect. *IFAC* **2017**, *50*, 15890–15895. [CrossRef]
35. Wang, Y.-F. Adaptive Job Shop Scheduling Strategy Based on Weighted Q-Learning Algorithm. *J. Intell. Manuf.* **2020**, *31*, 417–432. [CrossRef]
36. Trentesaux, D.; Pach, C.; Bekrar, A.; Sallez, Y.; Berger, T.; Bonte, T.; Leitão, P.; Barbosa, J. Benchmarking Flexible Job-Shop Scheduling and Control Systems. *Control. Eng. Pract.* **2013**, *21*, 1204–1225. [CrossRef]
37. Nouiri, M.; Bekrar, A.; Trentesaux, D. An Energy-Efficient Scheduling and Rescheduling Method for Production and Logistics Systems. *Int. J. Prod. Res.* **2020**, *58*, 3263–3283. [CrossRef]
38. Mirjalili, S. Genetic algorithm. In *Evolutionary Algorithms and Neural Networks*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 43–55.
39. Nouiri, M.; Bekrar, A.; Jemai, A.; Trentesaux, D.; Ammari, A.C.; Niar, S. Two Stage Particle Swarm Optimization to Solve the Flexible Job Shop Predictive Scheduling Problem Considering Possible Machine Breakdowns. *Comput. Ind. Eng.* **2017**, *112*, 595–606. [CrossRef]
40. Yuan, B.; Gallagher, M. A hybrid approach to parameter tuning in genetic algorithms. In Proceedings of the 2005 IEEE Congress on Evolutionary Computation, Edinburgh, UK, 2–4 September 2005; Volume 2.
41. Angelova, M.; Pencheva, T. Tuning genetic algorithm parameters to improve convergence time. *Int. J. Chem. Eng.* **2011**, *2011*, 646917. [CrossRef]
42. Vieira, G.E.; Herrmann, J.W.; Lin, E. Rescheduling Manufacturing Systems: A Framework of Strategies, Policies, and Methods. *J. Sched.* **2003**, *6*, 39–62. [CrossRef]
43. Qiao, F.; Wu, Q.; Li, L.; Wang, Z.; Shi, B. A Fuzzy Petri Net-Based Reasoning Method for Rescheduling. *Trans. Inst. Meas. Control.* **2011**, *33*, 435–455. [CrossRef]
44. François-Lavet, V.; Henderson, P.; Islam, R.; Bellemare, M.G.; Pineau, J. An Introduction to Deep Reinforcement Learning. In *Foundations and Trends in Machine Learning*; University of California: Berkeley, CA, USA, 2018; Volume 11, pp. 219–354.
45. Li, Y. Deep Reinforcement Learning: An Overview. *arXiv Preprint* **2017**, arXiv:1701.07274.
46. Brandimarte, P. Routing and Scheduling in a Flexible Job Shop by Tabu Search. *Ann. Oper. Res.* **1993**, *41*, 157–183. [CrossRef]
47. Nouiri, M. Implémentation d'une Méta-Heuristique Embarquée Pour Résoudre Le Problème d'ordonnancement Dans Un Atelier Flexible de Production. Ph.D. Thesis, Ecole Polytechnique de Tunisie, Carthage, Tunisia, 2017.
48. Bożejko, W.; Uchroński, M.; Wodecki, M. Parallel Hybrid Metaheuristics for the Flexible Job Shop Problem. *Comput. Ind. Eng.* **2010**, *59*, 323–333. [CrossRef]