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Dynamic and Sustainable Flexible Job Shop Scheduling Problem under Worker Unavailability Risk

Candice Destouet¹, Houda Tlahig¹, Belgacem Bettayeb² and Bélahcène Mazari³

Abstract—In the current context of Industry 5.0, sustainable scheduling has emerged as an evolution of classical scheduling, now integrating environmental and human-centric considerations. The objective is to strike a balance between economic, environmental, and societal concerns. Additionally, there is a growing need to enhance the resilience in the Industry 5.0 era, necessitating dynamic systems capable of reacting to unforeseen disruptive events. This paper introduces a multi-objective dynamic scheduling model designed to simultaneously minimize the makespan, the energy consumption, and a standardized ergonomic risk factor. The initial schedule is generated using a non-dominated sorting algorithm (NSGA-III), and in the event of worker absence during production, a rescheduling process is initiated. The choice of rescheduling strategy is determined using a Q-learning algorithm, allowing continuous improvement in the selection of the optimal strategy depending on the scenario. Results, derived from experiments conducted on literature instances, demonstrate the model’s effectiveness in swiftly generating new efficient schedules. The motivation for this research stems from the increasing demand for sustainable industrial practices that not only enhance productivity but also reduce environmental impact and improve worker well-being, thereby contributing to the development of more resilient and sustainable industrial systems.

I. INTRODUCTION

In manufacturing systems, Industry 5.0 is emerging as the logical progression from Industry 4.0. In [1], the authors propose an architectural design for Industry 5.0, illustrating how this paradigm builds upon existing digital transformation efforts while aiming to rectify the societal and ecological shortcomings of Industry 4.0. Industry 5.0 places emphasis on three primary aspects: environmental sustainability, human-centric approaches, and resilience [2]. This entails numerous consequences for decision-making across all levels within an industrial firm. More precisely, this necessity arises at the operational level, where production planning must address these three critical aspects [3]. Firstly, focusing on frugal utilization of machinery, energy, tools, and materials can contribute to improving the ecological sustainability of the system. Secondly, human considerations pose a far more complex challenge than the efficient and energy-saving use of resources. Ensuring the safety and well-being of workers involves accommodating their diversity and individual needs. Lastly, system resilience, defined as its ability to recover and return to its original functionality after a major

disruption, is a primary consideration. This capability is becoming increasingly valuable due to the proliferation of various crises and sources of disruption worldwide. Thus, in the event of disruptions during production, the system must promptly react and find rapid solutions. This paper addresses a Dynamic Flexible Job Shop Scheduling Problem that incorporates considerations of energy consumption and workers’ safety. The disruptions considered concern potential unpredictable periods of worker unavailability to factors such as lateness, illness, or other personal constraints. Section II gives a concise overview of the current state-of-the-art in sustainable and dynamic flexible job shop scheduling. Section III delineates the problem, develops the mathematical model, and outlines various rescheduling strategies to manage disruptions. Then, Section IV describes the methods used to solve the problem, including the non-dominated sorting genetic algorithm NSGA-III and a Q-learning algorithm. Finally, Section V presents the results obtained with instances from the literature, and Section VI provides the concluding remarks for our study.

II. LITERATURE REVIEW

The Sustainable Flexible Job Shop Scheduling Problem (SFJSSP) has been defined in [3] as a FJSSP with economical, environmental, human and resilience considerations. Firstly, the choice of machine can significantly impact the overall energy consumption, as certain machines may be more energy-intensive than others. Recent studies have increasingly focused on incorporating energy consumption data for machines and operations into scheduling algorithms [4][5]. Some research has even integrated strategies such as turn-on/off scheduling, as well as idle and stand-by modes for machines during inactive periods, effectively reducing energy consumption during downtime periods [6][7]. Additionally, significant energy is often expended in product transportation between machines, particularly with the use of automated guided vehicles. This has led to prompting efforts to optimize transport routes and methods to further reduce energy consumption [8]. Some other tasks such as setup times and loading/unloading operations contribute to energy consumption, while less frequently considered in scheduling models [9]. Most studies addressing energy consumption combine environmental objectives with economic ones, striving to strike a balance between the two through trade-off analyses.

To address the second pillar of Industry 5.0, various approaches exist for incorporating human factors into flexible job shop modeling. Initially, workers are often regarded as static, even marginalized resources, characterized by skills,

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costs, and capacity [10][11]. However, the new perspectives strive to place humans at the center of the production system. In recent studies, there has been a growing focus on factors such as safety indices, fatigue levels, and individual preferences, all aimed at improving worker well-being in the workplace [12][13]. Moreover, as satisfied, healthy and fulfilled workers are not only more productive but also are more likely to remain in their roles longer, thereby helping to strengthen the resilience of the entire system.

The resilience of a system refers to its ability to revert to its original state following a disruption. Thus, in the event of a disruption during production, the system must react promptly and provide a rapid solution to the issue. Common disruptions in a FJSSP include machine breakdowns, job insertions, uncertain processing times, and order cancellations [4][14][15][16]. To effectively address these disruptions, the model must be dynamic, capable of adapting to them. There are three types of dynamic models: i) completely reactive models, which generate schedules in real-time as jobs enter the system [14]; ii) proactive models, which often utilize fuzzy logic, probability, or stochastic parameters to anticipate and mitigate disruptions in advance [15]; iii) predictive-reactive models, which initially generate a schedule and adapt it during the process in response to disruptions [4].

In this paper, we introduce a model for Dynamic SFJSSP (DSFJSSP) considering human factors including safety and skills, as well as energy consumption by machines, transportation, and auxiliary equipment. Our approach employs a predictive-reactive dynamic scheduling model designed to address unexpected worker absences.

III. PROBLEM DEFINITION AND FORMULATION

A. The DSFJSSP description

The classical jobshop scheduling problem involves a set of J operations divided into K_j tasks that need to be processed in a predefined sequence on a set of machines. When tasks can be executed on various machines, it transforms into a Flexible Job Shop Scheduling Problem (FJSSP), composed of two sub-problems: i) determining the optimal allocation of a machine for each operation, and ii) establishing an optimal sequencing of operations assigned to each machine. Existing literature predominantly focuses on optimizing economic factors such as total process time, costs, and delays. However, the SFJSSP extends this scope to include environmental and societal considerations. In this context, we address the environmental aspect by minimizing energy consumed by machines, transport and auxiliaries equipment within the workshop. Incorporating the human element introduces additional complexity, firstly by necessitating the optimization of worker allocation for each operation, and secondly by incorporating concerns regarding worker safety and well-being. Consequently, we introduce a third objective: maximizing worker safety by minimising the maximum level reached on the OCRA index, developed by [17]. The OCRA index is a standardized measure that assesses the ergonomic risk for workers by evaluating the strain on their upper limbs. Human integration also requires considering uncertainty and

potential disruptions caused by workers. Personal constraints such as tardiness, temporary absences, or unforeseen emergencies can impact the production schedule. Whether a worker arrives late or is partially or entirely absent, these events can significantly impact the predefined schedule. Therefore, it is essential to find a strategy to adapt to these new constraints while minimizing disruptions to the initial schedule. Subsection III-B and III-C detail the mathematical model used to solve this problem and introduce various rescheduling strategies applicable in the event of disruption, specifically addressing the absence of an operator in our case.

B. Mathematical model

The sets, indices, parameters and decision variables used are :

\mathcal{W}	set of workers, $w = 1..W$.
\mathcal{M}	set of machines, $m = 1..M$.
\mathcal{J}	set of jobs, $j = 1..J$.
\mathcal{K}_j	set of tasks in j noted O_{kj} , $k = 1..K_j$.
\mathcal{T}	set of periods, $t = 1..T$.
d_t, f_t	starting and ending time of period t .
$p_{k_j w m}$	processing time of O_{k_j} on machine m with worker w .
$s_{k_j m k' j'}$	setup time on machine m between O_{k_j} and $O_{k' j'}$.
$tp_{m m'}$	transport time for a product between machines m and m' .
$t_{m m'}$	travel time for a worker between machines m and m' .
$e_{m m'}^{trans}$	energy consumption for transporting a product from m to m' .
e^{aux}	energy consumption of auxiliary equipment per unit time.
$ata_{k_j m}$	number of technical actions to execute O_{k_j} on machine m .
$pm_{k_j m}$	posture factor for executing O_{k_j} on machine m .
$rm_{k_j m}$	repetitiveness factor for executing O_{k_j} on machine m .
$fm_{k_j m}$	strength factor for executing O_{k_j} on machine m .
$arf_{k_j m}$	additional risks factor for executing O_{k_j} on m .
rcm, dum	factor for lack of rest and overall duration of repetitive tasks.
cf	constant frequency of technical actions by minute.
S_{k_j}, C_{k_j}	integer decision variables representing respectively the starting and ending time of O_{k_j} .
$R_{k_j w t}$	variable equal to the resting time for worker w after O_{k_j} .
$V_{t w}$	binary decision variable equal to 1 if worker w is assigned to period t .
$X_{k_j w m t}$	binary decision variable equal to 1 if O_{k_j} is executed on machine m by worker w on period t .
$Y_{k_j w k' j'}$	binary decision variable equal to 1 if O_{k_j} is done by worker w before $O_{k' j'}$.
$Z_{k_j m k' j'}$	binary decision variable equal to 1 if O_{k_j} is done on machine m before $O_{k' j'}$.
$N_{k_j m k' j' m'}$	binary decision variable equal to 1 if O_{k_j} is executed on machine m and $O_{k' j'}$ on machine m' .
C_{max}	makespan.
E	total energy consumption.
ET, EM, EC	total energy consumption for transport, operations and auxiliaries equipment.
$ATA_{w t}$	real number of technical actions for worker w on period t .
$RTA_{w t}$	recommended number of technical actions for worker w on period t .
$OCRA_{max}$	OCRA maximum for all workers and periods.

The mathematical model is described as a nonlinear program, with three objective functions and a set of constraints defined below. Please find more details in [18].

$$\min \{C_{max}, E, OCRA_{max}\} \quad (1)$$

The objective function (1) aims to minimize simultaneously the total process time (makespan), the total energy consump-

tion, and the maximum OCRA index.

$$C_{max} \geq C_{kj} \quad \forall j, k \in \mathcal{J}, \mathcal{K}_j \quad (2)$$

$$ET = \sum_j \sum_k \sum_m \sum_{m'} N_{kjm(k+1)jm'} \times e_{mm'}^{trans} \quad (3)$$

$$EM = \sum_j \sum_k \sum_m \sum_w \sum_t X_{kjwt} \times e_{kjwt} \quad (4)$$

$$EC = C_{max} \times e^{aux} \quad (5)$$

$$E = ET + EM + EC \quad (6)$$

The constraints defined in equation (2) establish the makespan as the maximum completion time of the schedule. Equations (3), (4) and (5) define the energy consumption for transport, machines, and auxiliaries equipment, respectively. Equation (6) computes the total energy consumption.

$$V_{tw} + V_{(t+1)w} = 1 \quad \forall t, w \in \mathcal{T}, \mathcal{W} \quad (7)$$

$$R_{kjwt} = 0.08 \times \sum_m X_{kjwt} \times p_{kjwt} \quad \forall t, w, j, k \in \mathcal{T}, \mathcal{W}, \mathcal{J}, \mathcal{K}_j \quad (8)$$

$$ATA_{wt} = \sum_j \sum_k \sum_m ata_{kjm} X_{kjwt} \quad \forall w \in \mathcal{W}, t \in \mathcal{T} \quad (9)$$

$$RTA_{wt} = (rcm \times dum) \sum_j \sum_k \sum_m cf \times pm_{kjm} \times rm_{kjm} \times fm_{kjm} \times arf_{kjm} \times X_{kjwt} p_{kjwt} \quad \forall t, w \in \mathcal{T}, \mathcal{W} \quad (10)$$

$$OCRA_{max} \geq \frac{ATA_{wt}}{RTA_{wt}} \quad \forall t, w \in \mathcal{T}, \mathcal{W} \quad (11)$$

The constraints formulated in equations (7) to (11) are the worker-related constraints. Equations (7) ensure that each worker is assigned to a period in alternating shifts. Equations (8) ensure that the rest times are respected. Equations (9), (10), and (11) compute the OCRA index for each worker.

$$S_{(k+1)j} \geq C_{kj} + \sum_m \sum_{m'} N_{kjm(k+1)jm'} \times tp_{mm'} \quad \forall j, k \in \mathcal{J}, \mathcal{K}_j \quad (12)$$

$$S_{k'j'} + (1 - \sum_m Z_{kjm k'j'}) M \geq C_{kj} + s_{kjm k'j'} \quad \forall j, j' \in \mathcal{J}, k, k' \in \mathcal{K}_j, \mathcal{K}_{j'} \quad (13)$$

$$S_{k'j'} + (1 - \sum_w Y_{k'jw k'j'}) M \geq C_{kj} + \sum_m \sum_{m'} N_{kjm(k+1)jm'} \times t_{mm'} + \sum_w \sum_t R_{kjwt} \quad \forall j, j' \in \mathcal{J}, k, k' \in \mathcal{K}_j, \mathcal{K}_{j'} \quad (14)$$

The constraints (12) to (14) are the precedence constraints for tasks of the same jobs, tasks assigned to the same machine and tasks assigned to the same worker, respectively.

C. Rescheduling strategies

When a disruption occurs within the system, such as a worker absence for a period, rescheduling becomes imperative. Consequently, we categorize the operations into three distinct sets: the completed operations, the incomplete operations, and the not yet started operations. The completed ones remain unchanged, while those that have not yet started or are incomplete require rescheduling. Three different rescheduling strategies can be used:

- Total rescheduling: both the operations that have not yet started and those incomplete that were being processed by the absent worker are rescheduled;
- Partial rescheduling: the machine and worker assignments for incomplete operations, as well as operations that are not yet started and not originally assigned to the unavailable worker, are retained. However, their starting times may be adjusted due to the disruption. As for the incomplete and not started operations assigned to the unavailable worker, each of them is reassigned to a new worker/machine pair, which potentially also leads to adjustments to their start times.
- Right shift rescheduling: the tasks that were incomplete or had not yet begun, initially assigned to the unavailable worker, are postponed until the worker becomes available again. Meanwhile, the sequence, machine, and worker assignments of other operations remain unchanged, although their starting times may be affected by the disruption.

Depending on the specific circumstances, the most effective strategy may vary. For our problem, it is crucial to select a strategy that minimizes disruption across three key aspects: the makespan, energy consumption, and the maximum OCRA. In order to obtain a strategy selection based on the circumstances, we adopted an approach based on the Q-learning algorithm, as described in Section IV.

IV. ALGORITHM DESCRIPTION

A. Initial schedule generation

The NSGA-III algorithm is used to generate the initial schedule. This algorithm operates with a population of solutions and can handle multiple objectives to converge towards solutions that are not dominated by others, thereby identifying the best options. To determine the final schedule for implementation, we select the solution that minimizes the average of our three objectives among the final population. For further insights into the algorithm's description and its application to our SFJSSP, readers may refer to [20].

B. Model training

To effectively respond to disruptions, we implemented the Q-learning method, introduced by [19] and used in [4], to select a rescheduling strategy. Given a state s_t , the Q-agent select an action a_t and gives a reward r_t of this pair state/action proportionally to the obtained outcome and update the Q-table. This iterative process ensures continuous improvement of the agent's knowledge. In our study, the

initial schedule serves as the environment for training the Q-agent. Over the course of 1000 ($tmax$) simulations, a worker is randomly selected at varying time intervals and durations. It defines the **state**. The state is determined by two parameters: i) the timing of the disruption occurrence, categorized into three phases, namely at the beginning, in the middle, or at the end of the initial schedule, and ii) the proportion of the duration of the operations that the worker was supposed to complete during his unavailability compared to the total duration of the operations that are still to be carried out by him. Based on the ranges of the two the previous parameters, Table I enumerates the 15 possible states. Subsequently, the Q-agent chooses a strategy to implement: either a total ($a1$), partial ($a2$), or right shift ($a3$) rescheduling. These strategies constitute the **actions** available to the agent. The selection of an action is facilitated by an epsilon-greedy strategy, which prioritizes exploration in the initial phases of the algorithm and transitions towards exploitation of acquired knowledge as the process evolves. Further elaboration on this strategy can be found in [20]. For the **reward** function, our three new objectives are analyzed: the updated makespan C_{max}^* , the updated energy consumption E^* and the updated maximum level of OCRA $OCRA_{max}^*$ obtained with the new schedule. The temporary reward r_{temp} is calculated as follows:

$$r_{temp} = \frac{1}{3} \times \frac{C_{max}^*}{C_{max}} + \frac{1}{3} \times \frac{E^*}{E} + \frac{1}{3} \times \frac{OCRA_{max}^*}{OCRA_{max}}$$

Note that the coefficient $\frac{1}{3}$ can vary according to the situation, giving more weight to one or another. Subsequently, r_t is derived from r_{temp} within the range of -5 to 5 , as in [4]. A smaller r_{temp} value corresponds to a larger reward. Next, the Q-table is updated with the following formula:

$$Q(s_t, a_t) = (1 - \alpha_t) \times Q(s_t, a_t) + \alpha_t (r_t + \lambda \times \max_a Q(s_{t+1}, a)),$$

with $\lambda = 0$ as only immediate rewards are considered, and $\alpha_t = 1 - 0.9 \times \frac{t}{T}$, where T is the total number of iterations. This adaptive α parameter ensures a pronounced influence on the Q-table during the early stages, gradually stabilizing over time. Table II represents the Q-table at each instant t .

TABLE I: State definition

	Proportion of disruption duration (%)				
	0-20	20-40	40-60	60-80	80-100
Beginning	$s1$	$s2$	$s3$	$s4$	$s5$
Middle	$s6$	$s7$	$s8$	$s9$	$s10$
End	$s11$	$s12$	$s13$	$s14$	$s15$

TABLE II: Q-table visualization

action/state	$s1$	$s2$...	$s15$
$a1$	$Q(s1, a1)$	$Q(s2, a1)$...	$Q(s15, a1)$
$a2$	$Q(s1, a2)$	$Q(s2, a2)$...	$Q(s15, a2)$
$a3$	$Q(s1, a3)$	$Q(s2, a3)$...	$Q(s15, a3)$

C. Rescheduling after a disruption

At this time, the system operates in online mode. If a worker is unavailable during the execution of the initial

schedule, the Q-agent is ready to respond to this disruption. Firstly, it identifies the current state, delineating the duration and timing of the worker's unavailability. Leveraging the information stored in the Q-table, the agent discerns the optimal action, i.e. the most suitable rescheduling strategy. Subsequently, the chosen action is implemented, leading to the generation of a new schedule. Both total and partial rescheduling procedures are executed using NSGA-III, while the right shift rescheduling is computed based on the rules outlined in Section III-C. The framework of the entire method is described by the flowchart in Figure 1. For a clearer understanding of the algorithm, please refer to the example in Section V-C.

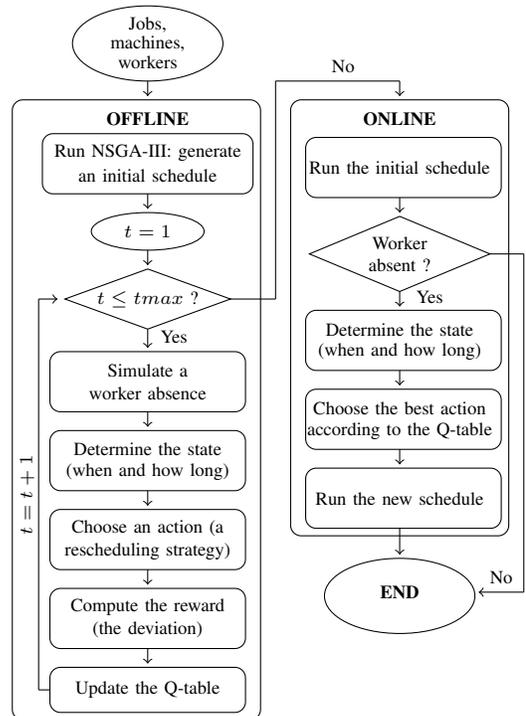


Fig. 1: Framework

V. RESULTS AND ANALYSIS

A. Instances

To test the efficiency of the method, we use different instances from literature that we have completed with data for transport/setup times, worker characteristics and energy consumption parameters. In this work, we present and discuss results obtained with two of them, namely kcm_4 from [21] and FJ_{15} from [22], which are detailed in Table III. To simulate a disruption, a worker is randomly selected at varying time intervals and durations.

B. Q-Table

After conducting 1000 simulations for both kcm_4 and FJ_{15} , we obtain a Q-Table containing the various rewards associated with each state/action pair. Table IV illustrates the optimal action for each state, denoting the action yielding the highest reward, applicable across both instances. If a

TABLE III: Instances composition

(a) Instances

Inst.	# jobs/tasks/mach./workers	proc. time (min)	energy (kW)
kcm_4	15/56/10/4	[1 – 85]	[4 – 15]
FJ_{15}	46/182/15/8	[1 – 20]	[15 – 20]

(b) Additional data

Parameters	value or range
energy for transport (e^{trans})	3.9 (kwh per time unit)
energy for auxiliaries (e^{aux})	1 (kwh per time unit)
transport (tp)/setup (s)/travel time (t)	[1 – 3] / [0 – 1] / [0.5 – 2]
workers' skills (p)	[0.9 – 1.3]
number of technical actions (ata)	[10 – 70]
posture multiplier (pm)	1-07-0.6-0.5
strength multiplier (fm)	1-0.85-0.65-0.35-0.2-0.01
repetitiveness multiplier (rm)	1-0.85-0.7
additional factors multiplier (arf)	1-0.95-0.9-0.8

disruption occurs at the beginning or middle of the process, partial rescheduling emerges as the preferred strategy. However, when the disruption arises during the last part of the process, the choice of rescheduling strategy varies based on the percentage of operations affected by the worker's unavailability. For disruptions affecting 0% to 40% of operations, right shift rescheduling is recommended. For disruptions affecting 40% to 80% of operations, total rescheduling is favored. Finally, if the worker's absence impacts 80% to 100% of their remaining operations, partial rescheduling is the preferred course of action.

TABLE IV: Best action for each state

s	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0														x	x
1	x	x	x	x	x	x	x	x	x	x					x
2											x	x			

C. Rescheduling results

In this section, we study three different scenarios:

- Scenario 1: a worker is late and will be unavailable at the beginning of the schedule;
- Scenario 2: a worker has to leave earlier and will be unavailable at the end of the schedule;
- Scenario 3: a worker has to leave in the middle of the process for some time.

We present the results obtained on these three scenario with kcm_4 instance. First, the initial schedule is presented in Figure 2. The makespan is equal to 92, the total energy consumption is 789 kWh, and the $OCRA_{max}$ to 1.93.

For the three different scenarios, the worker 2 will be unavailable for a certain amount of time. In the first scenario, he is unavailable from the beginning to the 44th minute, in the second scenario from the 69nd minutes to the end, and in the third scenario from the 50th to the 68th minutes. Table V presents the results of the three objectives obtained after each rescheduling strategy. For each scenario, the partial rescheduling gives the best result when averaging the three objectives. The time required to generate a new schedule

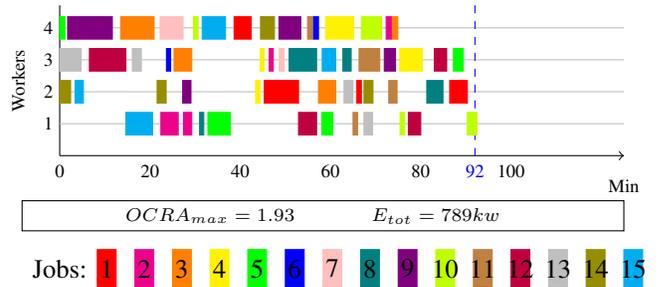


Fig. 2: Initial schedule

following a disturbance is less than 5 seconds for both total and partial rescheduling, and less than 3 seconds for the right shift strategy. However, it seems worth noting that training the model can be time-consuming, particularly due to the number of iterations needed to achieve convergence.

TABLE V: Objectives after rescheduling

	Scenario 1			Scenario 2			Scenario 3		
	Cmax	Energy	Ocra	Cmax	Energy	Ocra	Cmax	Energy	Ocra
T	140	977	1.44	114	864	1.53	174	954	1.19
P	108	805	1.85	106	802	1.62	103	788	2
R	126	823	1.93	106	803	1.93	107	804	1.93

Figure 3 presents an illustration of the three strategies applied during the first scenario, when worker 2 is late and arrives at the 44th minute. The total rescheduling strategy exhibits the poorest performance in terms of makespan and energy consumption, yet it excels in minimizing $OCRA_{max}$. However, this strategy may introduce significant deviations from the initial schedule. It is important to note that during the rescheduling phase, NSGA-III is executed with less optimal parameters than those used for the initial schedule, prioritizing speed to promptly address the disruption. Partial rescheduling yields favorable outcomes across all three objectives, notably in minimizing both makespan and energy consumption, with minimal deviation from the initial schedule. Throughout this process, the pair machine/worker remains consistent for all operations not assigned to the unavailable worker, while the sequence may be adjusted to accommodate the disruption. The right shift strategy maintains the same $OCRA_{max}$ because all machine/worker pairs remain unchanged for each operation. However, the disruption has an impact on the makespan and energy consumption, even though efforts are made to minimize the disparity between the initial and revised solutions. This strategy can prove effective, especially for minor disruptions.

VI. CONCLUSION

In this paper, we address a Dynamic Sustainable Flexible Job Shop Scheduling Problem, which considers economic, environmental, and human factors. At the beginning of the proposed approach, the NSGA-III algorithm is employed to derive an initial schedule that balances these three aspects, optimizing the makespan, energy consumption, and $OCRA$ index simultaneously. Subsequently, three rescheduling strategies are employed for the random event of worker

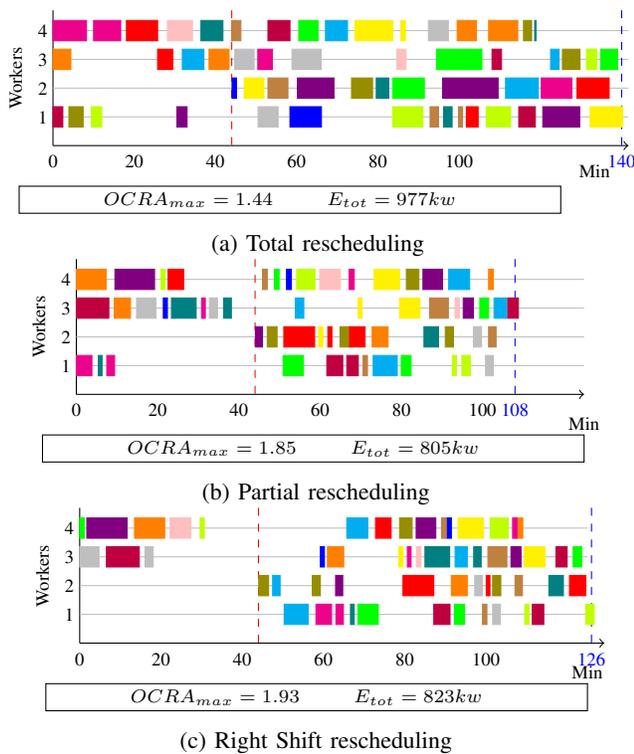


Fig. 3: The three strategy applied in scenario 1

unavailability. The optimal strategy is selected using a Q-learning method dependently on the timing and occurrence of the disruption. The results suggest that partial rescheduling emerges as the preferred strategy for most disruptions. Nevertheless, right shift and total rescheduling prove to be efficient when disruptions occur towards the end of the schedule, for shorter and longer durations, respectively. Each method yields a new schedule in less than 5 seconds for the tested instances. However, the tested instances do not precisely mirror real-life environments, which are often larger with more operations, machines, workers, and longer overall process. In such case, the algorithm's learning phase can be time-consuming. Our future research will focus on enhancing our algorithms to handle larger instances, comparing them with other methods and exploring additional disruptions, such as machine breakdowns and new job insertions.

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