A Decison-Making Approach for Job Shop Scheduling with Job Depending Degradation and Predictive Maintenance

C. Fitouri *,**,*** **N. Fnaiech** * **C. Varnier** ** **F. Fnaiech** * **N. Zerhouni** **

* *Université de Tunis, ENSIT, LR13ES03 SIME, 1008, Montfleury, Tunisia*
(e-mails: fitouricyrine@yahoo.fr, fnaiechnader@yahoo.fr, fnaiech@ieee.org)
** *Femto-st institute, UBFC, ENSMM, CNRS, 25000, Besançon, France*
(e-mails: christophe.varnier@ens2m.fr, Noureddine.Zerhouni@ens2m.fr)
*** *Université de Tunis El Manar, École Nationale d'Ingénieurs de Tunis*
(ENIT), 1002, Tunis, Tunisia

Abstract: Maintenance is a strategic function in a company. It aims to ensure the proper functioning of an equipment. It no longer has the sole objective to repair a system but also to anticipate and prevent its failures. Recently, new failure prediction techniques have emerged. They provide information on the real-time condition of equipment and its remaining useful life (RUL). Thus, new methods of decision-making based on the analysis of these recent developments can be considered. Indeed, this paper presents a heuristic method for solving the makespan and the cost of a resumable job shop problem while predicting and preventing failures. It is based on the elimination of duplication that may exist between the different operations at a given point in time, while selecting a single operation and shifting the others at the end of the execution thereof. The best selection of the operation to assign on the machine depends on the effectiveness of the decision rule used for scheduling. The proposed method has been successfully tested on some experimental benchmarks and it allows a satisfactory resolution of relatively important problem in a reasonable time.

Keywords: Scheduling problem, Predictive maintenance, Decision-making, Makespan, Maintenance cost, Prognostic.

1. INTRODUCTION

Economic pressures are forcing companies to be more successful in a highly competitive environment driven by market laws. The industrial activity of a company is dependent on its decisions which acquire an increasingly importance within the organization. One of these decisions arises the maintenance.

The maintenance function includes the specification of maintenance policies, the decision to intervene and the scheduling of maintenance periods. It aims to reduce the frequency of breakdowns and maximizing the operational availability of an equipment in order to minimize the periods of inactivity, as a result of voluntary or accidental service interruptions.

Here, the job shop scheduling problem (JSSP) of production and predictive maintenance is addressed.

There is a wide body of literature dealing with the JSSP. It is considered among the most complicated problems in industry (NP-hard). It has been studied by lot of researchers using different algorithms and optimization methods such as branch and bound algorithms for Jones et al. (2001); the shifting bottleneck heuristic for Adams et al. (1988); dispatching rules for Chiang and Fu (2007), and other techniques based on tabu search for Glover (1990); simulated annealing for Van L. et al. (1992); neural networks for Yahyaoui et al. (2011) and genetic algorithms for Omar et al. (2006).

In the classical JSSP, machines are always considered 100% available. It is not the case in real world. Machines have indeed to be maintained. Then, a new scheduling problem appears with additional constraints. In the literature, the latter problem is known as scheduling problem with unavailability and two cases are presented.

The first one is the deterministic case, when maintenance periods are fixed in advance. There are only some papers studying scheduling problems with deterministic availability constraints in job shop environment. Ma et al. (2010) made a survey in this topic. They listed for each typology of scheduling problem (single machine, parallel machines, flow shop, open job and job shop) complexity results, exact algorithms and approximation algorithms. For the job shop case, they cited some works using branch and bound algorithm, priority rules and genetic algorithm and also a generalization algorithm to solve a problem of resumable and nonresumable jobs and, crossable and non-crossable unavailability periods.

The second one is the stochastic case, when unavailability periods are due to machine breakdowns. Few works were done. One can cite Harrath et al. (2012) who proposed a multiobjective genetic algorithm based method for job shop scheduling problem where machines are under preventive and corrective maintenance activities.

Recently, maintenance policies are moving towards a dynamic aspect. In fact, new prognosis techniques have emerged (Tobon-Mejia et al. (2012)). They permit to provide information on the real-time state of an equipment. Also, they allow to estimate the time before the failure on a given machine, which is called the Remaining Useful Life (RUL).

A reactive and dynamic scheduling is then feasible. One can cite some of works that were carried out in this field. Ouelhadj and Petrovic (2009) defined the problem of dynamic scheduling and provided a review of the state of the art of recently developing research on dynamic scheduling. Duenas and Petrovic (2008) developed an approach which is based on generating a predictive schedule that absorbs the effects of uncertain disruptions. Lou et al. (2012) presented an approach to scheduling in the dynamic uncertain manufacturing environments, which involves two stages: the proactive scheduling stage and the reactive scheduling stage. Park et al. (1996) proposed an interactive scheduling expert system, IOSS (Intelligent Operations Scheduling System), which performs both predictive and reactive scheduling.

In this framework, researchers have been interested by the problem of predictive maintenance scheduling. Varnier and Zerhouni (2012) proposed a mixed integer programming model for a flow-shop problem with the makespan and maintenance delays objective. Horenbeek and Pintelon (2013) presented a dynamic predictive maintenance policy Keywords: for multi-component systems that minimizes the long-term mean maintenance cost per unit time. Pan et al. (2012) proposed a single-machine-based scheduling model incorporating production scheduling and predictive maintenance.

In this paper, an approach for solving the job shop scheduling problem of production and predictive maintenance is proposed. The main purpose of the approach is to make sure that the best scheduling decision is taken at each time, in order to minimize the makespan and the total cost of maintenance.

The remaining sections of this paper is organized as follows: section 2 presents the considered problem. The proposed heuristic is described in section 3. The results are discussed in section 4. Finally, section 5 gives some concluding remarks.

2. NOTATIONS AND PROBLEM STATEMENT

The Job shop is a workshop production where jobs have to be scheduled. This problem is stated as follows: consider n jobs. Each job has to be processed on m machines following different sequence. Each machine can perform only one job at a time. The problem consists in defining the execution order of tasks on each machine, while respecting the sequence constraints. The different operations of each job are denoted by O_{ijk}, which is the jth operation of job J_i that is processed on the machine M_k, and the processing time of O_{ijk} is noted p_{ijk}. Besides, some tasks O_{ijk} can be resumable. Then, resumable and nonresumable operations occur in the same schedule.

In the problem tackled, machine are subjected to wear and tear. We assume that machine are monitored and a prognostic module can be used to manage predictive maintenance. This policy involves a simultaneous scheduling of production and maintenance tasks. Each machine has a current level of degradation (between 0.0 – no degradation and 1.0 – total degradation) at the beginning of the schedule. The prognos-

Table 1.

Used notations in the JSSP of production and predictive maintenance

Symbol	Designation
$J = \{J_1, J_2, \ldots, J_n\}$	Set of n jobs
$M = \{M_1, M_2, \ldots, M_m\}$	Set of m machines (resources)
O_{ijk}	The jth operation of job J_i to be processed on machine M_k
p_{ijk}	Processing time of the operation O_{ijk}
s_{ijk}	Starting time of the operation O_{ijk}
X_{ijk}	equal to 1 if operation O_{ijk} is resumable equal to 0 if operation O_{ijk} is nonresumable
RUL_{ik}	RUL of a job J_i to be assigned on machine M_k
δ_{min}	Minimum threshold of degradation
δ_{max}	Maximum threshold of degradation
Δ_{ijk}	Given degradation after assigning the operation O_{ijk}
Δ_{M_k}	Degradation of machine M_k
$[s_k{}^x, e_k{}^x]$	Interval of the xth unavailability on machine M_k
p_{M_k}	Duration of a proposed maintenance task on machine M_k
w_{ij}	Weight of the operation O_{ij} at t depending on the decision rules and its Δ_{ij}

tic module is able to give the remaining useful life, denoted RUL_{ik}, of the machine M_k depending on the task O_{ijk} performed (figure 1(b)). The prognostic model will be detailed in section 2.3. Moreover, we suppose that after a maintenance operation, the machine is considered as good as new. Note that, the maintenance duration p_{M_k} is known and fixed. And, there is only one type of maintenance.

2.1 Notations

The different common notations and abbreviations used along the paper for mathematical modeling and for the proposed heuristic are given in table 1.

2.2 Job shop scheduling

The constraints of a JSSP, commonly known in the literature, are as follows:

Constraints:

- Sequence Constraint:
    to be manufactured, jobs are forced to follow an ordered sequence of operations. It is necessary in a feasible schedule that:
$$s_{ijk} \geq s_{i(j-1)q} + p_{i(j-1)q} \qquad (1)$$
    where s_{ijk} is the starting time of O_{ijk}
- Resource Constraint:
    In order to avoid the resource conflict, for all couple of operations O_{ijk} and O_{ylk} processed on the same machine M_k, it is required that:
$$[s_{ijk}, s_{ijk} + p_{ijk}] \cap [s_{ylk}, s_{ylk} + p_{ylk}] = \emptyset \qquad (2)$$

2.3 Predictive maintenance scheduling

The prognostic points to an existing process in the context of predictive maintenance of industrial systems. It aims to estimate the Remaining Useful life (RUL) and the risk of existence or subsequent emergence of one or more failure modes (Gouriveau and Medjaher (2011)).

RUL model for one operation: Each operation O_{ijk} that has to be performed on machine M_k induces a degradation that depends on their breaking strength. Then, we propose to model the degradation as follows: we assume that the remaining useful life RUL_{ik} of a machine M_k achieving job J_i is known. RUL_{ik} represents the time during which the machine is able to produce the job without breakdown. We assume that the RUL value is certain.

As a consequence, one can convert the RUL information in term of degradation (see figure 1(a)). For an operation O_{ijk} on machine M_k, Δ_{ijk} will be the amount of degradation imposed.

$$\Delta_{ijk} = \frac{p_{ijk}}{RUL_{ik}} \tag{3}$$

RUL model for one machine: Since the degradation impacts are not the same for all operations, the sequence in which operation are performed influence the time before predictive maintenance. The figure 1(b) shows how degradation evolved in function of the operation sequence. In the problem considered we assume that degradation of a machine should never exceed the threshold value δ_{max}. A predictive maintenance operation has to be scheduled before this value. It is also assumed that a maintenance operation is never scheduled under a degradation level δ_{min}. The degradation Δ_{ijk} is always lower than δ_{max} for all operations.

2.4 Objective

In this article, the problem deals with the optimization of two main objectives. On the one hand, the best production schedule is the one with minimal makespan. On the other hand, for the efficiency of the predictive policy proposed, maintenance operations should occur if it is possible just before the maximal degradation threshold.

Consequently, we are seeking to minimize the makespan (C_{max}) and in the same time to minimize the maintenance cost which is defined in equation 4 for a machine M_k (figure 2)

$$C_{M_k} = C_k^f + C_k^v(\Delta_{M_k}(t)) \tag{4}$$

Where C_k^f is a fixed cost and

$$C_k^v(\Delta_{M_k}(t)) = \begin{cases} a_e(\Delta_{M_k}(t) - \delta_{max}) & if \ \delta_{min} < \Delta_{M_k}(t) < \delta_{max} \\ 0 & if \ \Delta_{M_k}(t) = \delta_{max} \end{cases}$$

Note that a_e is the cost of advance per unit of time.

The total maintenance cost is given by :

$$C_M^T = \sum_{k=1}^{m} C_{M_k} \tag{5}$$

3. THE PROPOSED HEURISTIC

The aim of the proposed heuristic is to act on the machine as close as possible to its breakdown period. Our approach is based on the elimination of duplication that may exist between the different operations using the same machine M_k at a moment t. To prevent the overlap of operations, eleven shifting rules are proposed.
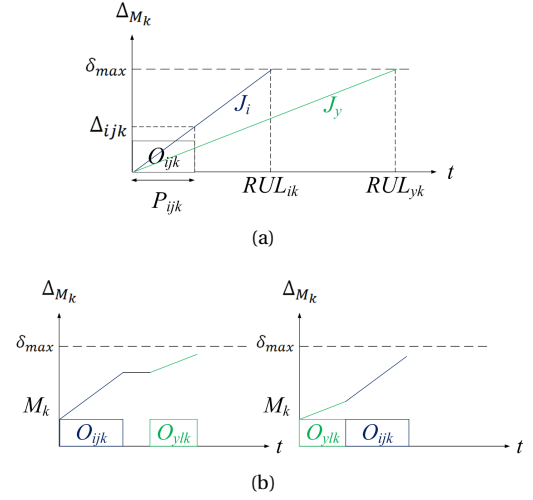

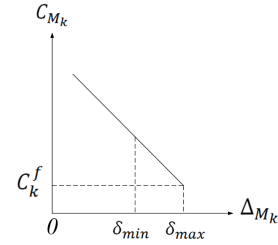Fig. 1. RUL model for an operation O_{ijk} and for a machine M_k

Fig. 2. Curve of the maintenance cost

3.1 Shifting rules

To address the overlap of operations at each point in time t, shifting rules are considered according to the status of the machine and the characteristic of the chosen operation.

Shifting rule 1: If the chosen operation O_{ijk} is characterized by

$$\Delta_{ijk} + \Delta_{M_k} < \delta_{max} \tag{6}$$

then this operation will be performed and the rest of the operations will automatically be shifted at the end of that operation by Δ_{t1}. see (figure 3)

Shifting rule 2: If the chosen operation O_{ylk} is characterized by

$$\Delta_{ylk} + \Delta_{M_k} > \delta_{max} \ and \ X_{ylk} = 1 \tag{7}$$

then $O_{(ylk)'}$ will be performed such as

$$\Delta_{(ylk)'} + \Delta_{M_k} = \delta_{max} \tag{8}$$

and the rest of the operations, including $O_{(ylk)''}$, will automatically be shifted at the end of that operation by Δ_{t2} as illustrated in (figure 4)

Shifting rule 3: If the chosen operation O_{ylk} is characterized by

$$\Delta_{ylk} + \Delta_{M_k} > \delta_{max} \ and \ X_{ylk} = 0 \tag{9}$$

then we look at the subsequent operations and check if there is one operation that can be assigned totally or partially without exceeding δ_{max}.

Shifting rule 4: At some subsequent moment, it exists a subsequent operation to be assigned on the machine, then the available operations at a point in time t will be transferred

from moment t to moment $t+1$ which is defined by Δ_{t4}. See (figure 5)

Shifting rule 5: At some subsequent moment, it does not exist an operation to be attributed on the machine. Here, a proposal of predictive maintenance action is imposed.

Shifting rule 6: Let's define t_f as the final date of the latest operation assigned to the machine. If

$$t_f + \mathrm{P}_{\mathrm{M}_k} > t \qquad (10)$$

then the available operations will be shifted by Δ_{t6} as shown in (figure 6).

Shifting rule 7: If

$$t_f + \mathrm{P}_{\mathrm{M}_k} < t \qquad (11)$$

then the selected operation will be assigned and the others will be shifted by Δ_{t7} as shown in (figure 7).

Shifting rule 8: If at the moment t of scheduling, the list of operations is vacant, then nothing occurs and the next moment $t+1$ will be considered.

Shifting rule 9: If at the moment t of scheduling, the list of operations on standby is within an interval of unavailability, then the list will automatically be shifted by Δ_{t9} as illustrated in (figure 8).

Shifting rule 10: If at the moment t of scheduling, the list of operations on standby is in phase with the execution of another operation, here the list will automatically be shifted at the end of that operation by Δ_{t10} as shown in (figure 9).

Shifting rule 11: When an unspecified operation O_{yl} is shifted by a time Δ_{t11}, the following operations $\{O_{y(l+1)}, O_{y(l+2)}, O_{y(l+3)}, ...\}$ of the same J_y are delayed by the same Δ_{t11}. See (figure 10)

Note: All those shifting rules imply an adjustment of starting times of the operations in order to obtain a feasible solution, which respects all constraints. The chosen operation in the shifting rules cited above, depends on some decision rules which will be described at the sequel.

Each operation O_{ijk} is characterized by (s_{ijk}, p_{ijk}, RUL_{ik}, X_{ijk}) and has a variable w_{ij} associated with it. At each time t, the possibility to have more than one operation, which respect the different constraints, to be allocated on the machine M_k can occur. The operation will be selected according to the decision rule used for scheduling (when w_{ij} is minimized). Six decision rules are proposed to that end. Each problem is resolved by one decision rule. once finished, the same problem will be resolved by another decision rule until all six rules are applied.

The decision rules, which are a kind of priority rules, are defined as follows:

- Shortest processing time (SPT): Select the operation that has the SPT.
- Longest processing time (LPT): Select the operation that has the LPT.
- Lowest total cost (LTC): Select among the operations, the one if assigned, it gets the LTC.
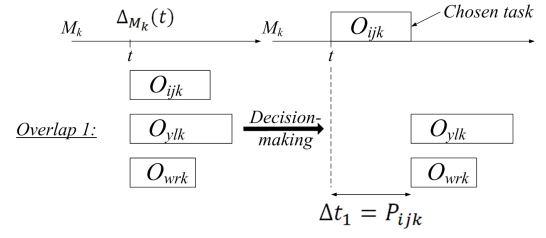- Biggest percentage of degradation (BPD): Select the operation which relays the biggest value of Δ_{ijk}.

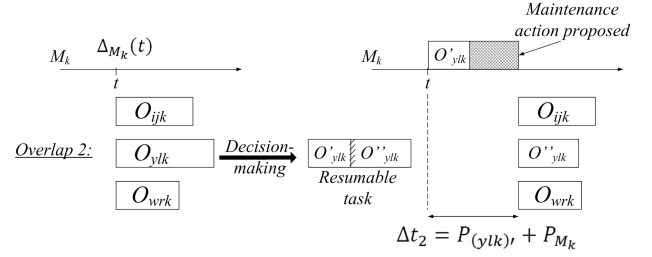Fig. 3. Assignement of the operations according to the shifting rule 1

Fig. 4. Assignement of the operations according to the shifting rule 2
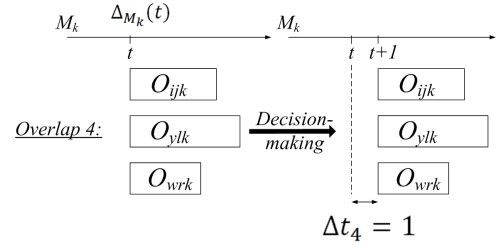
Fig. 5. Assignement of the operations according to the shifting rule 4

- Smallest percentage of degradation (SPD): Select the operation which relays the smallest value of Δ_{ijk}.
- Reducible makespan (RMK): Select the operation which can reduce or maintain the makespan of the total schedule.

The effect of the choice reflects on:

- Production (the instantaneous change in the value of C_{max} when shifting operations each time),
- Maintenance (the given degradation when an operation is chosen and the additional costs generated by the proposal of a predictive maintenance).

3.2 General algorithm

At the beginning, all resources are considered 100% available, in order to initialize the starting times of operations. So, a scheduling with a temporary starting times is obtained. The rule of the initialization of starting time values is illustrated in Yahyaoui et al. (2009).

The general algorithm of the proposed heuristic is summarized in figure 11.

4. EXPERIMENTAL RESULTS

In order to evaluate the proposed heuristic, various decision rules have been performed on some job shop scheduling problems.

M_k $\Delta_{M_k}(t)$ M_k

Maintenance action proposed

Overlap 6: O_{ijk} O_{ylk} O_{wrk} → *Decision-making* → O_{ijk} O_{ylk} O_{wrk}
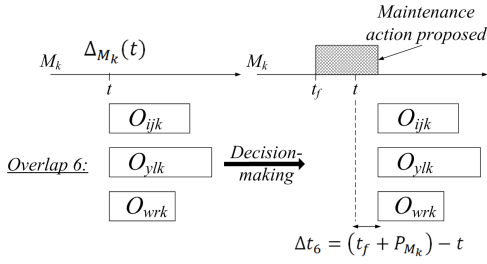
$$\Delta t_6 = (t_f + P_{M_k}) - t$$

Fig. 6. Assignement of the operations according to the shifting rule 6

Maintenance action proposed

M_k $\Delta_{M_k}(t)$ M_k O_{wrk} ← *Chosen task*

Overlap 7: O_{ijk} O_{ylk} O_{wrk} → *Decision-making* → O_{ijk} O_{ylk}

$$\Delta t_7 = P_{wrk}$$

Fig. 7. Assignement of the operations according to the shifting rule 7

M_k s_k^x t e_k^x M_k s_k^x t e_k^x

Overlap 9: O_{ijk} O_{ylk} O_{wrk} → *Decision-making* → O_{ijk} O_{ylk} O_{wrk}

$$\Delta t_9 = e_k^x - t$$

Fig. 8. Assignement of the operations according to the shifting rule 9

M_k O_{ijk} M_k O_{ijk}

Overlap 10: O_{ylk} O_{wrk} O_{zvk} → *Decision-making* → O_{ylk} O_{wrk} O_{zvk}

$$\Delta t_{10} = (S_{ijk} + P_{ijk}) - t$$

Fig. 9. Assignement of the operations according to the shifting rule 10

Δt_{11} t

$O_{y(l-1)}$ O_{yl} $O_{y(l+1)}$ Δt_{11} $O_{y(l-1)}$ O_{yl} $O_{y(l+1)}$

Decision-making

Overlap 11:
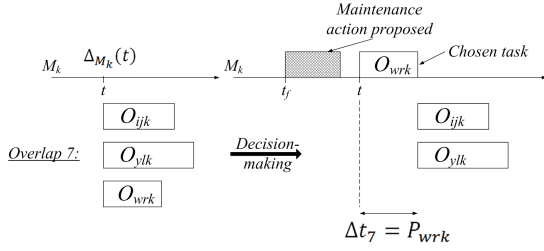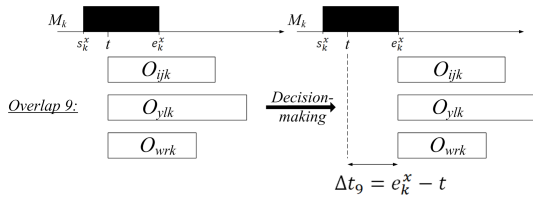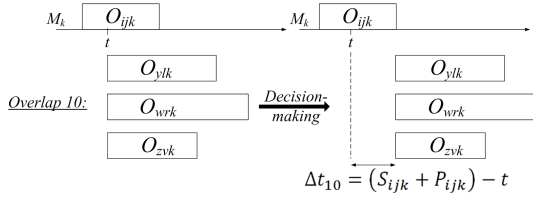
Fig. 10. Assignement of the operations according to the shifting rule 11

4.1 Data generation

Random problems are generated in order to test our proposed heuristic. Three problems with different sizes are proposed, which are 5 jobs/5 machines, 5 jobs/10 machines, and 10 jobs/3 machines. Any problem can be solved by our heuristic method, with the condition that it respects constraints. For the simulation, the value of δ_{min} is fixed at 75% and δ_{max} is fixed at 95%. Then, we have generated 10 instances of each problem size.

Initialization
$\forall\, i = 1,...,n \quad \check{s}_{i1} = 0$
$\forall\, i = 1,...,n \text{ and } j = 2,...,m \quad \check{s}_{ij} = \sum_{l=1}^{j-1} (p_{il})$
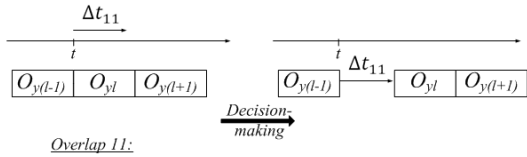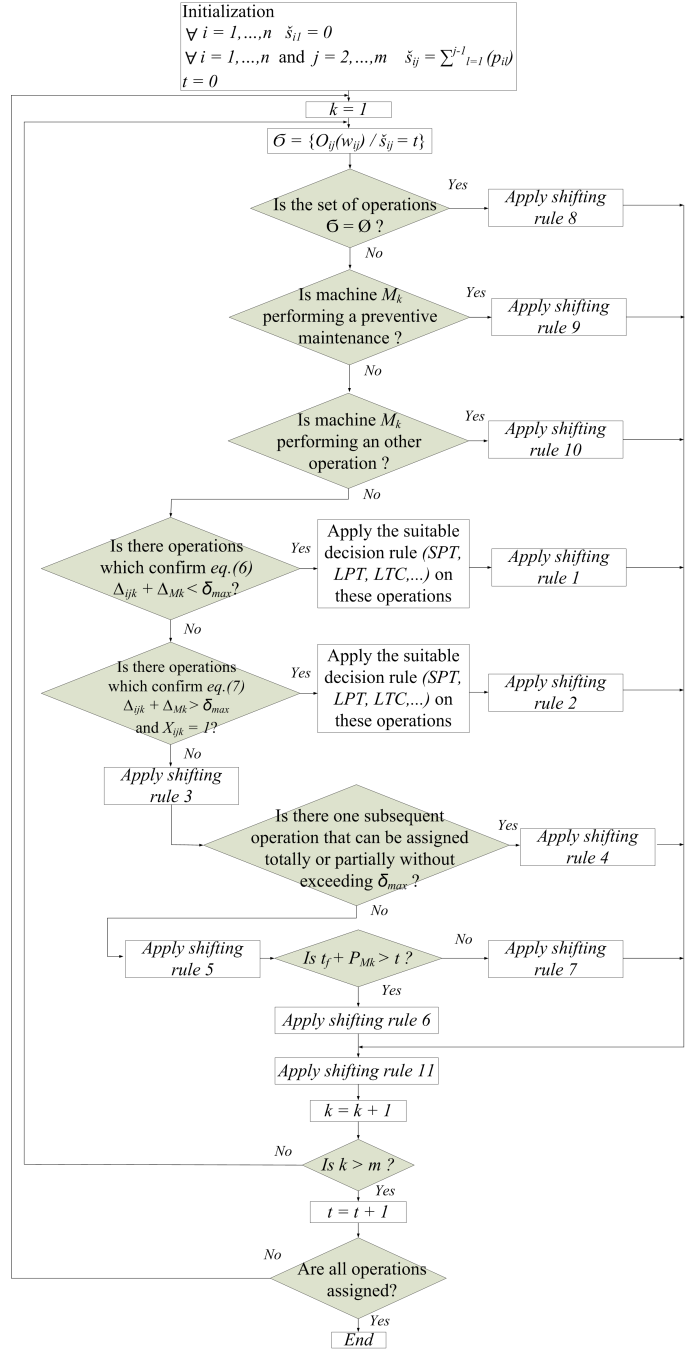$t = 0$

$k = 1$

$\sigma = \{O_{ij}(w_{ij}) \,/\, \check{s}_{ij} = t\}$

Is the set of operations $\sigma = \emptyset$? — Yes → Apply shifting rule 8

No ↓

Is machine M_k performing a preventive maintenance ? — Yes → Apply shifting rule 9

No ↓

Is machine M_k performing an other operation ? — Yes → Apply shifting rule 10

No ↓

Is there operations which confirm *eq.(6)* $\Delta_{ijk} + \Delta_{Mk} < \delta_{max}$? — Yes → Apply the suitable decision rule *(SPT, LPT, LTC,...)* on these operations → Apply shifting rule 1

No ↓

Is there operations which confirm *eq.(7)* $\Delta_{ijk} + \Delta_{Mk} > \delta_{max}$ and $X_{ijk} = 1$? — Yes → Apply the suitable decision rule *(SPT, LPT, LTC,...)* on these operations → Apply shifting rule 2

No ↓

Apply shifting rule 3

Is there one subsequent operation that can be assigned totally or partially without exceeding δ_{max}? — Yes → Apply shifting rule 4

No ↓

Apply shifting rule 5 ← Is $t_f + P_{Mk} > t$? → No → Apply shifting rule 7

Yes ↓

Apply shifting rule 6

Apply shifting rule 11

$k = k + 1$

Is $k > m$? — No (loop) / Yes ↓

$t = t + 1$

Are all operations assigned? — No (loop) / Yes ↓

End

Fig. 11. General algorithm of the proposed heuristic

Table 2.

Comparison between the applied decision rules in term of C_{max} value

Examples	M.C_{max}					
	SPT	LPT	LTC	BPD	SPD	RMK
5/5	85,6	89,3	83,9	89,1	86,1	80,9
5/10	129,7	135,6	130,6	144,7	132,5	127,9
10/3	139,3	137,8	111,8	136,3	127,1	143

4.2 Discussion

For the simulation example, we have applied the six decision rules on the three problems 5/5, 5/10, and 10/3. Table 2 and Table 3 represent an average of 10 instances of each problem size. M.C_{max}, M.Deg and M.TCost are respectively mean C_{max}, mean degradation cost and mean total cost.

<div align="center">Table 3.</div>

<div align="center">Comparison between the applied decision rules in term of cost</div>

Examples	SPT		LPT		LTC		BPD		SPD		RMK	
	M.Deg	M.TCost	M.Deg	M.TCost	M.Deg	M.TCost	M.Deg	M.TCost	M.Deg	M.TCost	M.Deg	M.TCost
5/5	6951,62	11383,12	7732,37	12794,47	7967,01	12118,51	7088,99	12241,09	7695,56	12157,06	8532,25	12513,75
5/10	11802,7	17085,7	13556,2	19625	12688	18081	15682,1	22280,9	12313,7	18336,7	12513,9	17589,7
10/3	14878,6	26504,7	10883,2	22226,9	7761,2	16706,3	10792,6	22619,1	10602,2	21189,7	15732,4	27790,5

For the 5/5 and 5/10 problems, RMK provides the best results in term of C_{max} value, while SPT provides the best results in term of cost.

For the 10/3 problem, LTC provides the best values of C_{max} and costs.

The two tables show that for the same problem, the applied decision rules provide different solutions. One can conclude that the solution of one problem depends on the choice of the decision rule. The selected solution will be that which has the minimal cost and C_{max} values.

5. CONCLUSION

In this paper, we proposed a decision-making approach for solving job shop scheduling problem with predictive maintenance constraint. In fact, a simultaneous scheduling of production and maintenance, without exceeding the maximal threshold of degradation, was developed.

Indeed, shifting rules depending on the resumable or nonresumable characteristic of the operation, and the degradation of the machine were listed and explained. These latter permit the disposal of the duplication which may exist between the different operations.

Different decision rules were proposed to classify and to select one of the available operations at each point in time.

Once all decision rules applied, the selected solution for the JSSP of production and predictive maintenance is the one that has the minimal cost and C_{max} values.

Further works would be continued after these first results. We are seeking a combination of the different decision rules in order to achieve better results. We are also working on the on-line decision-making. A comparative study will be considered, particularly between maintenance policies.

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