A POST-PROGNOSTIC DECISION APPROACH FOR PRODUCTION AND MAINTENANCE PLANNING

O. Bougacha[1*], C. Varnier[1], N. Zerhouni[1] and S. Hajri-Gabouj[2]
[1]*FEMTO-ST institute, Univ. Bourgogne Franche-Comté, ENSMM, CNRS,*
Besançon, France
omar.bougacha@femto-st.fr,
christophe.varnier@femto-st.fr,
noureddine.zerhouni@femto-st.fr

[2]URAII, National Institute of Applied Science and Technology
University of Carthage, Tunisia
sonia.gabouj@insat.rnu.tn

ABSTRACT

At first, Prognostics and Health Management (**PHM**) was interpreted as a new trend of Condition Based Maintenance (**CBM**) to schedule, in a more effective way, preventive maintenance actions. Lately, PHM is being used in operational decisions like choosing the appropriate mission to execute, planning logistics actions or defining the control parameters. In most of the previous studies, a single Remaining Useful Life (**RUL**) value was estimated by the prognostic module and integrated in the decision module regardless of the effect of already made decisions on the system health and consequently on its future RUL values. Consequently, this paper presents a jointly maintenance and operational decision-making approach for multi-component systems on a rolling decision horizon by iteratively integrating the new available RUL values to update the tasks schedule including maintenance interventions. The aim of this paper is to emphasize the need of integrating the feedback loop of the effects of already made decisions on the monitored system in the process of prognostics process. The obtained results are then compared to other methods of jointly scheduling operational and maintenance decisions like Moore algorithm combined with CBM.

Keywords: Prognostics and Health Management, Production and Maintenance Scheduling, Remaining Useful Life, Post-Prognostic Decisions

[*] Corresponding Author

1 INTRODUCTION

The implementation of smart manufacturing systems in the industry 4.0 made human machine cooperation, monitoring and process control, and high reliability and availability of the machines, major assets of the modern factories. The digital transformation of the manufacturing industry triggered a high evolution in the production process and the maintenance process. Although these two processes are interdependent, the works that jointly optimize the production scheduling and the maintenance planning of the manufacturing systems are often focused on classical preventive maintenance.

During the last decade, Prognostics and Health Management (**PHM**) has known an increased interest. It was designed to improve the link between failure occurrence and systems' life management. It was essentially used as a new trend of Condition Based Maintenance (**CBM**), which explains the similarity between the PHM process and the CBM system architecture as defined by Lebold and Thurston [1].

Post-Prognostics Decisions are the results of the decision making process of PHM. These decisions consist in integrating the prognostics information in the resolution of an optimization problem. Generally, the optimization problem is about maintenance schedule definition with the objective of minimizing the cost and avoiding failures. Several works in literature dealt with Post-Prognostics decisions. By considering the type of the proposed decisions, one can classify these decisions into three categories;

1. **Maintenance Decisions:** the main idea is to choose which component/system needs to be maintained and at which moment depending on the remaining useful life of components or systems. Such kind of decisions is applied for several industrial domains: transport Rodrigues et al. [2], manufacturing Yang et al. [3], Tian and Liao [4], aerospace Balaban and Alonso [5], Wind-Turbines Lei and Sandborn [6].
2. **Operational Decisions:** Considering the prognostic information, one can also decide to change the way to use the systems. Three kinds of adjustments can be consider:
    a. **Production and Tasks assignment:** it consists in defining the good fitting between the tasks that should be realized and the system degradation levels. This was studied for manufacturing scheduling Skima et al. [7], path planning or for UAVs fleets De Medeiros et al. [8].
    b. **Automatic Control:** if the system is controllable, one can monitor and modify the control parameters to adapt the system usage Pereira et al. [9], Grosso et al. [10].
    c. **Logistics:** To fulfill its purpose and during its lifetime, any systems needs an amount of support in setting the right provisions of row materials, in-processing products and spare parts. These provisions and logistics movements are based on the systems health state and its estimated RUL in order to reduce the cost of unnecessary storage of row materials and spare parts Julka et al. [11], Cui et al. [12]. Therefore, the system obtains the right amount of row materials and/or spare parts according to its capacity to produce or its need to be maintained.
3. **Mixed Decisions:** This category is the combination of the aforementioned categories. One can jointly optimize the mission assignment and the maintenance interventions like in De Medeiros et al. [13]. One can also find a compromise between producing and maintaining the machines as in Fitouri et al. [14].

One can notice that most of the literature works focus on the maintenance decisions, and very few once studied the mixed decisions. Thus, one can say that the use of prognostics in mixed decisions is becoming a new trend in PHM context to fulfill the needs of the industry 4.0. In order to highlight the importance of such decisions, this paper will focus on jointly planning production activities and maintenance interventions based on prognostics information.

In literature, the papers found concern various applications and consider different configurations of machines and different granularity levels. Some have considered multiple machines systems. Jin et al. [15] proposed a framework for planning maintenance activities for a geographically distributed manufacturing system. Haddad et al. [16] proposed a new real-option model to optimize the maintenance of offshore turbines based on prognostic indications. Others considered single machine systems. Tian et Liao [4] considered the maintenance scheduling of a multiple components single system based on its the failure probability. Lei et Sandborn [6] optimized the maintenance decision-making based on PHM information for a single wind turbine. In this primary work, we are focusing on a specific configuration of system. We are interested in studying the case of multiple components in a single machine. Camci [17], proposed a method for scheduling maintenance actions on a similar system, with the assumption that the machine is running with the same production profile and in the same conditions. Van Horenbeek et Pintelon [18], studied a similar system to Camcis' [17] but they only supposed that the machine is running in the same production profile where the different operational conditions where modeled by the use of random failure thresholds that follows a Weibull distributions. The common point of these two papers is that they both only considered maintenance decisions. As for our case, we consider both maintenance and operational decisions on a multiple components single machine. By doing so the assumption of constant production profile and constants operational conditions are eliminated.

The organization of the paper is as follows: the high inter-dependency between prognostics and decision-making is presented in Section 2. In sections 3, we describe the proposed framework its concept, its related definition and the developed algorithm. Then we present the application of this method on a case study, the different tests scenarios and results synthesis in section 4. Finally, conclusions on this study and some future works are given in Section 5.

2 LINKS BETWEEN PROGNOSTICS AND DECISION-MAKING

Basically, in the context of PHM we have a system equipped with sensors to monitor either the system health or some components health. Sensors data will be first acquired and stored, then they have to be processed to clean errors and to extract features. This is done in the observation phase. Next, the obtained preprocessed data is feed into an analysis phase, where fault detection module, diagnosis module and most importantly prognostics module provide with the Remaining Useful Life (RUL) and/or Health Indicators. Based on these indicators a decision could be proposed in a decision support phase. This basic loop is presented in the full-line blue arrows in figure-1. The application of the chosen decision (the dashed-line orange arrow that represents the feedback of the decision on the system) will change the systems state and consequently the sensors signals (the dashed orange arrow). This will results in a different preprocessed data and thus a new RUL value (noted RUL'). With a new RUL value the set of possible decisions will change and thus this will result in a new decision (noted Decision'). And so on, each time when a new decision is made, the system state will change and new possible decisions are available. This proves the high inter-dependency between the prognosis and the decision-making modules.

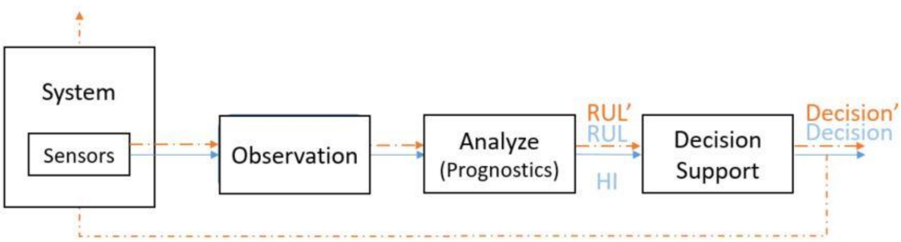

Figure 1: The natural PHM Process

Most of the literature papers presents a decision making process based on a single RUL estimation. These papers propose the scheduling of maintenance activities or tasks assignment over a finite decision horizon using a static prognostic information. Which leads us to conclude that this PHM is said to be an open loop process and it can be modeled by the block diagram presented in figure-2. A common problem with this approach is that the obtained results presents a high level of uncertainty caused by the unknown future loads of the system. In addition to that, the longer the decision horizon is the lower the prognostic precision becomes.

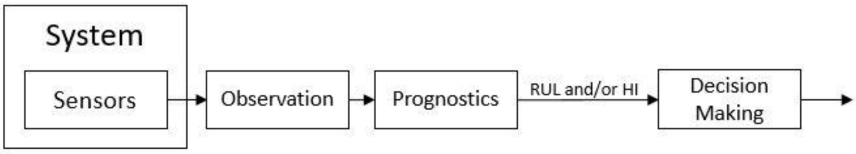

Figure 2: The Ancient PHM Process

To eliminate these drawbacks we fixed our objective to upgrade the PHM process from an open-loop process into a closed-loop one. The new process is supposed to dynamically estimate the RUL values and emphasize the relation between the prognostics and the decision-making modules.

3 FRAMEWORK OF THE PROPOSED APPROACH

3.1 Definitions

To guarantee the consistency of the approach, we first define the following terms:

- **Rolling Horizon:** To study the influence of already made decision on the system, we are going to work on a rolling decision horizon. In this case, at each RUL estimation, we schedule tasks and maintenance action for the duration of the rolling horizon. By the next RUL prediction, the rolling horizon is shifted and the schedule is updated by adjusting the remaining tasks in the decision, scheduling the new available tasks and the possible maintenance interventions as shown in figure-3.
- **Elementary Decision:** it is a single decision that could be either an operational one by choosing which task to execute next with which parameters, or a maintenance intervention by selecting the components to maintain.
- **Partial Decision:** it is the sequence of executed elementary decisions between two consecutive predictions of remaining useful life.
- **Global Decision:** it is the sequence of planned elementary decisions over the rolling horizon.
- **Step:** it is defined as the moment when new data is available, the prognostic module is run to estimate the new value of RUL, and a new schedule is elaborated.
- **Period:** The decision horizon is divided into smaller time units. These time units are called periods. They can be a day, a week or a month depending on the studied system and its specifications.

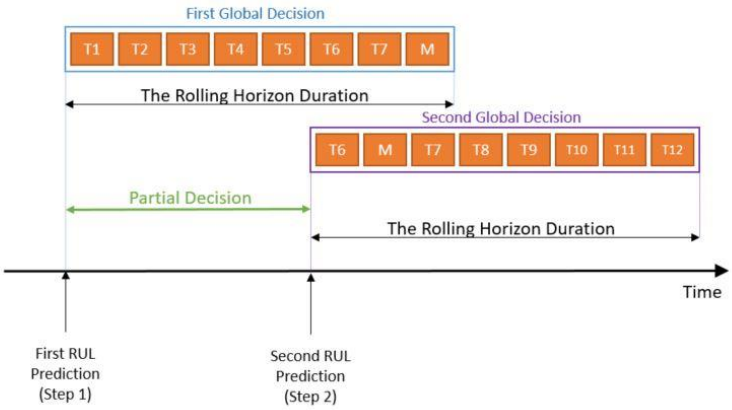

Figure 3: Illustration of the terms

Figure-3 shows an illustration of the predefined terms. Elementary decisions are represented by the orange boxes. At step-1, i.e. the first RUL prediction, a first global decision is constructed over the rolling decision horizon. This global decision is then executed until a second RUL value is estimated at step-2. Between step-1 and step-2 a part of the first global decision is executed; this part is called partial decision. At step-2, the rolling horizon is shifted and a second global decision is constructed by updating the remaining elementary decision of the first global decision and by adding the new available tasks.

3.2 Concept

First we considered the dynamic aspect of the RUL estimation by periodically execute the PHM process. At each step, we are going to build global decision over a predefined decision horizon out of elementary action. Therefore, the proposed approach consists in iteratively building and updating global decisions by integrating newly available prognostics information. The iterative aspect of the approach is represented by the physical loop in red in figure-4.

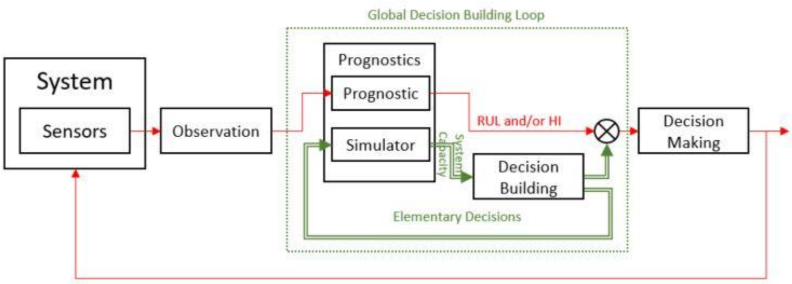

Figure 4: Physical and Decisions Loops of the Proposed Approach

Global decisions are built by scheduling operational tasks with their corresponding parameters and eventually maintenance actions if needed. The obtained schedule is based on the system capability to fulfil the proposed elementary actions. Our proposed approach consists in adding inside the prognostic phase a simulator that is able evaluate the evolution of the system degradation for the available decisions. Once the task to execute, i.e. the elementary decision, is selected, the virtual system (simulator) state is updated. Then the next possible actions is evaluated and so on until the duration of the rolling horizon is reached. The output of the decision building is a global decision defined as a sequence of elementary decision with their corresponding degradation evolution. This decision loop was represented in green double-lines in figure-4. The resulted global decision and the actual RUL value and/or health indicators (i.e. the value estimated by the prognostic module) are then jointly feed to the decision making process that will apply the sequence of elementary decisions on the system. Thus the red feedback of the decision making process on the system.

3.3 Algorithm

As defined by Goebel et al. [19], a decision-making process is an optimization problem. This can be explain by the fact that usually there are many possible actions that could be taken, where each action has a cost, a way of implementation and an effect on the system. The objective of a decision support module is to choose the most adequate actions that satisfies the problem constraints and that optimizes a predefined objective function. To solve these optimization problems we can use different techniques like exact algorithms (like linear programming, branch and bound procedure) or heuristic algorithms (like evolutionary algorithms - genetic algorithm, ant colony optimization or particle swarm optimization).

In our case, we need to construct a global decision out of elementary ones by taking into consideration and by anticipating the effect of the selected ones on the system. Each time we select a new elementary decision the set of possible next elementary decision changes. Also, the global decisions can contain various number of elementary decisions. These two features lead us to eliminate the genetic algorithms approach. Optimal branch and bound algorithms are known to give exact solutions but they are also known for their exponential computation time for solving NP-hard problems. Then we proposed to use a modified Ant Colony Optimization approach to build our global decisions. It is based on the Ant Colony Optimization algorithm defined by Dorigo and Caro [20].

Figure-5 represents the algorithm used for this approach. At each step we are going to initiate the ant colony. Then each ant will consider all possible elementary actions from the current state of the system. They will evaluate the system's capability to fulfil the possible actions i.e. they will run a simulation of the system with the considered action and check if the final state degradation level. Each ant will then select a random local decision of its list and update its virtual system state. The ant repeat the same actions until all of the ants reach the end of the decision horizon. Then we will increment the number of cycles, select the best global decision and update the pheromone quantities on the local decisions. We check then if the number of cycles have reached the predefined limit or not. If not the ants are set to go through another cycle, otherwise the algorithm is stopped and the best global decision is transmitted.

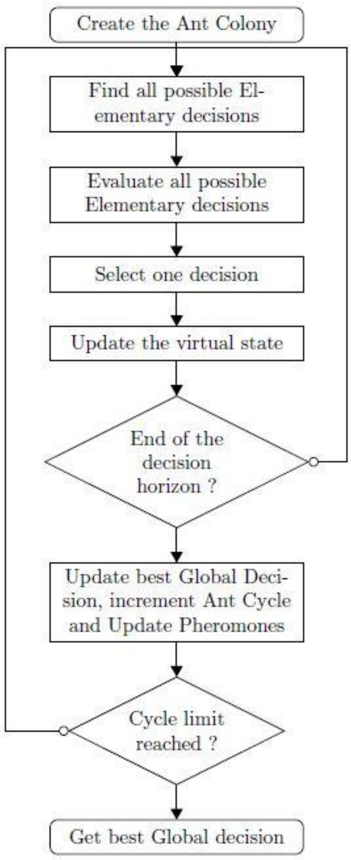

Figure 5: The process of the used algorithm

4 APPLICATION

The previous approach was applied on a production scheduling problem.

4.1 Motivation

Camci [17], scheduled the maintenance activities for a single machine system over a finite decision horizon. The studied machine has several components that were subject to degradation. The computed schedule contained more than one maintenance action for each considered component. These actions were scheduled based on a single prognostic information with the implicit assumption that the system is always running with the same production profile in the same operational conditions. Even if such assumptions were true the fact of executing a maintenance activity over the system can change the end-of-life prediction of the systems and so the next scheduled maintenance activities can be either a premature maintenance or a late maintenance. Although the influence of the decision on the system are obvious, Camci didn't consider that in his work. As does most of the papers in literature that studied the post-prognostic decisions. This is proved since all the works were based on a single RUL value. Which means that decisions over a long horizon were built based on the assumption that decision making will not affect the current RUL. On the other hand, Van Horenbeek et Pintelon [18] considered, the feedback of the decisions on the system. This was demonstrated by re-planning the obtained schedule whenever a new prognostics information are available and by considering a rolling decision horizon. Since the various possibilities of systems configurations and granularity levels, we choose to start working on a system similar to Camci's and Van Horenbeek and Pintelon's. So for this primary approach, we are going to consider the case of single machine composed of *L* non-identical components. Such systems are considered complex where the contained components can be characterized with three types of dependencies: structural dependency, economic dependency and stochastic dependency by Nicolai and Dekker [21]. Structural dependence is when a component stops due to maintenance or failure all the dependent components stops. Economic dependence signifies that maintaining dependent components together will cost less than maintaining them separately. Stochastic dependence is when a component fails/degrades causes the failure/degradation of all dependent components. Compared to Camci [17] and Van Horenbeek and Pintelon [18], we supposed that the system can operate with different operational profiles. The operational profiles can be related to one or more parameters of the system (for example the speed of a motor can be used to defines operational profiles for the motor). This assumption allows us to demonstrate the effects of changing operational profiles on the systems RUL evolution. Each of the system component has a degradation model. In the aforementioned papers these models are supposed to be influenced only by the machine activity if it's working or not. To bring closer the degradation evolution to reality we assumed that the degradation is influenced by the task to execute and its size and the operational profile with which the task will be executed. The degradation of a component is, also, related to the execution of a task, i.e. when the system is idle the degradation level is assumed to be stable.

4.2 Problem statement

Classically, PHM problems were based on minimizing the cost of maintenance because post-prognostic decisions back then mostly considered only maintenance schedule. Lately and with PHM becoming more involved in operational decisions the PHM problem soon became a multiple objectives optimization problem. For example, Zhang et al [22], integrated prognostics information in path planning applied on a rover that experiences a reduced remaining charge of its battery. In this example, the cost function of the optimization problem considered three factors; mission duration, terrain difficulty and the degradation of the battery. The objective is to get to a finish point while minimizing a cost function influenced by one or more factors.

In this paper, we are going to consider a mixture between maintenance and operational decisions applied to an industrial manufacturing system. This explains the high influence of the industrial context on the problem statement. Our objective is to find the best compromise between producing with different speeds and maintaining the machine in order to maximize the factory benefits. Thus, we consider the scheduling problem of I production orders on a multiple components single manufacturing machine system. The machine is composed of L serials components i.e. when a component fails the whole system fails. In this application, only structural dependencies are considered. Each production order i has a quantity Q_i of a certain product type to produce, a release date r_i, a due date d_i and a deadline D_i. The orders are available at their release date and no preemption is allowed. The machine is able of producing J different products where each product j is characterized by its sell price P_j per unit, a coefficient of influence s_j^l on component's l degradation and a lateness penalty per time unit LP_j if the order containing the product j is delivered after its due date d_i and before its deadline D_i. The machine has K possible production profiles. Each profile k is characterized by a cost C_j^k of producing one unit of product j for $j \in J$ and a duration of producing one unit with this profile (regardless the type of the product).

The elementary decisions are either produce a production order i with a profile k or a maintenance action for part l. The main objective, as described in equation (1), is to schedule elementary decisions in the way to maximize the benefits of the factory over an M-Steps simulation horizon.

$$max \sum_{m\in M} B_m = max \sum_{m\in M} G_m - C_m \quad \textbf{(1)}$$

Where: $\begin{cases} G_m \ is\ the\ gain\ of\ the\ m^{th}\ step\ its\ expression\ is\ detailed\ in\ equations\ 2\ and\ 3 \\ C_m\ is\ the\ cost\ of\ the\ m^{th}\ step\ its\ expression\ is\ detailed\ in\ equations\ 4\ and\ 5 \end{cases}$

The global decision's gain of the m^{th} step :

$$G_m = \sum_n G_n \quad \textbf{(2)}$$

With G_n the gain of the n^{th} elementary decision is defined as :

$$G_n = \begin{cases} Q_i * P_j\ for\ production \\ 0\ for\ maintenance \end{cases} \quad \textbf{(3)}$$

The global decision's cost of the m^{th} step :

$$C_m = \sum_n C_n + LOP * (A - U - M) \quad \textbf{(4)}$$

With A is the duration of the rolling horizon, U is the time used for production, M the time used for maintenance and LOP is a penalty on the lost opportunity and C_n the cost of the n^{th} elementary decision is defined as follows :

$$C_n = \begin{cases} Q_i * C_j^k + u_i * Q_i * LP_j\ for\ production \\ \sum_{l\in PM}(M_l + PRUL_l * REP_l)\ for\ maintenance \end{cases} \quad \textbf{(5)}$$

With :

$$u_i = \begin{cases} 1\ if\ i\ is\ late \\ 0\ Otherwise \end{cases} \quad \textbf{(6)}$$

$$REP_l = \begin{cases} RUL_{th} - RUL_l\ if\ RUL_{th} < RUL_l \\ 0\ otherwise \end{cases} \quad \textbf{(7)}$$

$PRUL_l$ is a penalty on the not used portion of the maintained component.

4.3 Approach comparison

If we consider the problem without prognostics information, then the cost of an elementary decision will be defined as following :

$$C_n = \begin{cases} Q_i * (C_j^k + u_i * LP_j) & Production \\ \sum_{l\in PM} M_l & Maintenance \end{cases} \quad \textbf{(8)}$$

With the gain of an elementary decision remains unchanged as defined in equation (3), in this case, we can consider minimizing the cost of the decisions as an objective to optimize the objective equation (1). As defined in equation (8), the only variable we can affect by modifying the schedule is the u_i, i.e. if the order is tardy or not. Thus we need to minimize the number of tardy jobs. In this context, Moore [23] developed an algorithm that minimizes the number of tardy tasks in the case of a single machine with non-preemptive tasks.

Since our objective is to manage the system life and health, it is important to add maintenance decisions. That's why we combined Moore algorithm with a classic CBM algorithm. Where at the start of each period we check if there is a necessity to schedule a maintenance action for the system or not. The need for a maintenance action is determined by comparing the actual degradation level of each component with a threshold. If one or more degradation level exceed the threshold for maintenance a maintenance action is scheduled at the beginning of the period then the rest of the duration is scheduled with Moore algorithm to obtain the global decision, otherwise we directly schedule production. If the system fails before the next health inspection a corrective maintenance action takes place. Corrective maintenance costs more that scheduled maintenance and takes more time. This Algorithm will be noted **MCBM** in the rest of this paper.

4.4 Problem generation

For this numerical application we assumed that the machine is capable of producing four product types with three different production profiles (i.e. Low, Medium and High speed). Each of the component has a degradation model, for simulation purposes, we supposed that the degradation model follows an exponential function. Equation (9) represent the degradation model of component l while executing the task i with the production profile k.

$$D_{l,i,k}(x) = a_l * (e^{b_l * x * S_i^l * PP_k} - 1) \quad \textbf{\textit{(9)}}$$

Where a_l and b_l are two parameters related to the component they define the evolution of the exponential function. S_i^l is the coefficient of the task i severity on component l. PP_k is a coefficient that represents the influence of production profile k on the component degradation. It is supposed that the production profile influence the different component with the same rate. An example of this degradation model is shown in figure 6.

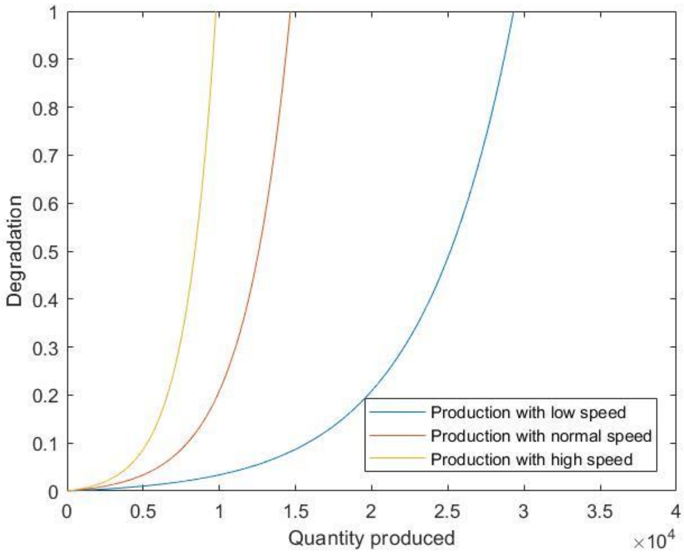

Figure 6: Example of a degradation evolution for a component under different production profiles

The defined algorithm for the proposed approach is influenced by some parameters related to the input data. Of these parameters, we choose the following ones to variate into different test cases:

- The degradation profile of the components: Three cases were considered; rapidly degrading components where the RUL of a new component is less than 4000 product, normally degrading components where the RUL of a new component is between 4000 and 10000 products and slowly degrading components with RUL is more than 10000 products.
- The initial state of the system: Randomly generated initial degradation levels for each component.

- The quantity to produce in the orders and consequently the number of orders per time unit: Three categories were considered; small tasks where $Q_j \in [10, 50]$, medium tasks with $Qi \in [30, 100]$, and large tasks where $Q_j \in [100, 200]$.

To evaluate the approach different cases and combinations of these parameters were considered.

5 RESULTS

This section will be divided into two subsections. In the first subsection, we will compare the two proposed algorithms, i.e. the approach and the MCBM, over only one decision horizon. In the second subsection, we will present the results over the simulation duration.

5.1 The proposed approach vs the MCBM

To compare the proposed approach to the MCBM algorithm we defined some performance indicators. For instance, we will use the Cost of a decision over the rolling horizon and the benefit of the global decision. Since the Moore algorithm is supposed to minimize the number of tardy jobs, we will then compare the number of delayed orders, and we will compare the number of missed orders. To compare the performance of the maintenance planning we will monitor the number of corrective maintenance. To compare the general performance of the considered algorithm we will follow the evolution of the utilization of the machine (noted U(%)) and the produced quantity (noted QP).

The above-mentioned indicators are measured over one-step of global decision construction for 100 test case. The obtained results are divided according the test type i.e. small, medium and large tasks. In addition to that, the indicators are evaluated in terms of minimum, average and maximum values. A summary of the results is given in table (1).

Table 1: Single Step Performance Comparison.

		Small Tasks		Medium Tasks		Large Tasks	
		Proposed A.	MCBM	Proposed A.	MCBM	Proposed A.	MCBM
Cost	Min	1209	1354	1235	1541	1190	1470
	Avg	1489	1739	1486	1754	1717	1830
	Max	1811	2534	1776	2925	2310	3765
Benefit	Min	4767	3807	4769	3930	3790	2939
	Avg	5508	4869	5654	4783	5851	4481
	Max	6149	5504	6523	5923	7739	6257
Delayed Orders	Min	25	30	9	9	3	4
	Avg	30.12	35.66	12.26	13.75	4.53	6.5
	Max	37	42	15	18	7	9
Missed Orders	Min	8	5	3	2	1	2
	Avg	14.75	8.94	5.82	4.27	2	2.52
	Max	19	15	8	7	4	4
Corrective M.	Min	0	0	0	0	0	0
	Avg	0	0.7	0	0.75	0	0.64
	Max	0	2	0	2	0	2
U(%)	Min	91	72	96	79	94	76
	Avg	96.8	85	97.9	87.5	97	85
	Max	99.6	90.6	99.9	92.66	99.58	92
Quantity Produced	Min	1375	1304	1407	1434	1389	1367
	Avg	1475	1532	1498	1574	1592	1533
	Max	1613	1631	1633	1668	1884	1656

In table 1, we can notice that in every case the cost of the schedule obtained by the proposed approach is lower than the one provided by the MCBM. According the equations (4) and (5), the cost of a global decision is influenced by the following reasons:

- **The Produced Quantity:** The produced quantity intervene directly in the definition of the cost of a decision. In addition, we can here notice that in the cases of small and medium orders the produced quantity by the proposed approach is lower than those produced by MCBM. In the case of large tasks, the quantity produced is higher than those produced by the MCBM but the cost is still lower and this is caused by the other factors. If we compare the quantity produced and the cost of decision in the case of large tasks to the cases of small and medium tasks, we can easily see the influence of the produced quantity on the cost.
- **Tardy Orders:** The number of tardy orders has a direct influence on the cost of the decision. Although the Moore algorithm is developed to minimize the number of tardy orders, still the number of tardy jobs in the schedules of the proposed approach is lower than the one obtained by the MCBM. The extra tardiness in the MCBM results are caused by the unplanned maintenance actions. Also the fact that the approach consider different operational profiles in the other hand the MCBM operates with only the average profile.
- **Maintenance Cost:** The maintenance cost in this studied case is influenced by two reasons:
  - **Corrective Maintenance:** Corrective maintenance tends to be more costly than planned maintenance actions. From the table we can see that the MCBM solutions presents a high risk of corrective maintenance compared to the proposed solutions that does not contain unplanned maintenance.
  - **Premature Maintenance:** Premature maintenance is when a component is maintained while it can still produce. For instance, figures 7 and 8 represent respectively the evolution of the degradation level of component 3 in one of the tests. At this level, we are only interested in the degradation level when the maintenance is performed. In the case of MCBM the maintenance was done at 0.84 while in case of the proposed approach we reached 0.94 of degradation before maintenance.
  - **Machine Utilization:** The time spent where the machine is available but idle for lack of jobs is considered as a lost opportunity. The use of an operational profile that takes more time to produce will extend to time needed to fulfill an order and this will reduce the time spend when the machine is ready to produce but no order is available or the remained time before the end of the period does not allow the execution of an order. Moreover, in all the presented cased we reached a level of utilization more important than the one obtained by the MCBM.

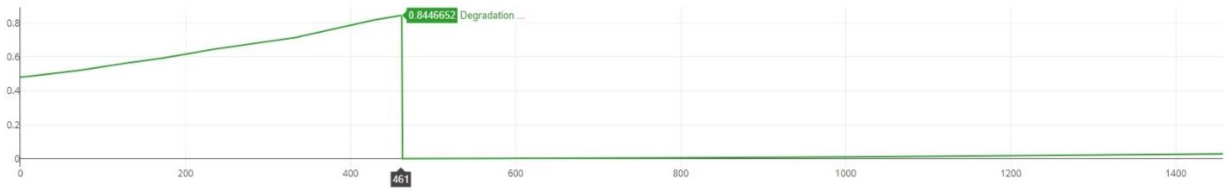

Figure 7: The degradation of component number 3 under the MCBM method

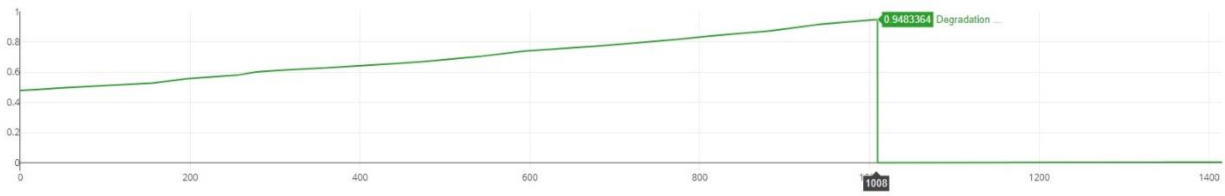

Figure 8: The degradation of component number 3 under the Proposed Approach

In addition, we notice that the benefits of each of the cases is higher using the proposed approach. As the benefits defined as the difference between the gain and the cost of a decision, a part of the explanation of this results is that MCBM solution are more costly. The other part is the value of the gain. As mentioned in the problem statement, each product j has a different sell price. The MCBM is developed in a way to indirectly minimize the cost by minimizing the number of tardy jobs, but the algorithm does not consider the type of the product, the quantity of the order or at which price the order will be sold. On the other hand the ant colony algorithm consider these facts and has an objective to prioritize orders with the higher gain and then to figure out how to produce them at lower cost.

As for the missed orders, the number is higher with the proposed approach in the cases of small and medium tasks. Although the larger the tasks the lowest the number of missed orders until we reach a lower number than the one obtained by the MCBM in case of large tasks. This has to do with the consideration of different operational profiles. In the proposed approach, it is better to produce smaller number of orders with low speed and deliver them in time then to produce more orders ending up by causing many tardy jobs and causing more degradation to the machine. The use of different profiles allows us to manage better the health of the machine. This can be seen by comparing figures 7 and 8 where in the case of the proposed approach we reached the 0.84 degradation level at approximately the double of products needed to get the component at the same degradation level with the MCBM.

In this subsection, we showed one-step results comparison between the proposed approach and the MCBM. As a conclusion, the proposed approach is more interesting in term of benefits cost in every case. It has a drawback of the number of missed orders when it is about small or medium tasks. When the approach presents it full performance at large tasks.

5.2 Synthesis

After comparing the two algorithms over one-step of simulation, we will now study the cumulative effect on the obtained results. In that order, figure 9 presents the different evolution of benefits obtained by the proposed approach and those obtained by MCBM over the duration of the simulation. Through this figure, one can easily notice that the integration of prognostics information in the decision process with a closed loop approach guarantee a more important benefits than using the MCBM. One notes that the larger the tasks the bigger the difference between the benefits of the approach and those of the Moore algorithm.

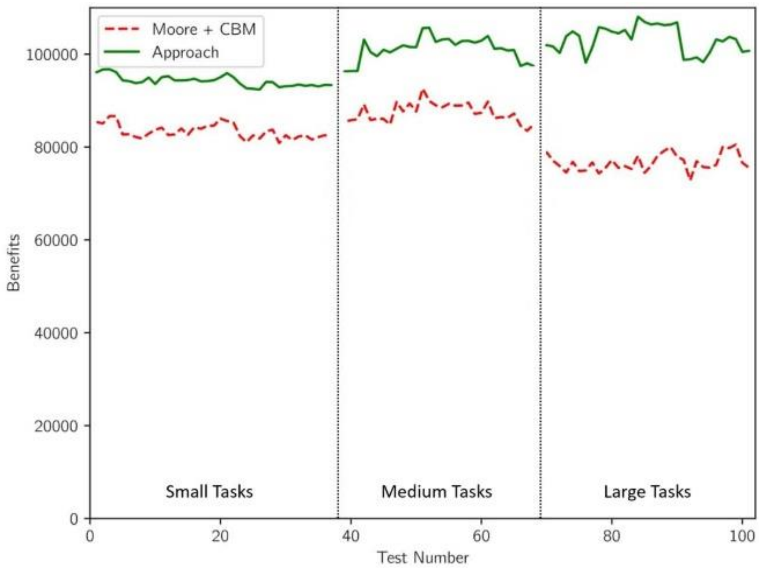

Figure 9: General evolution of benefits

Table 2 presents a summary of the average obtained results. All the three scenarios presents a higher machine utilization rate with the proposed approach and a lower maintenance and lost time rates compared to the MCBM. In the case of small and medium tasks the number of products made under the proposed approach is slightly less than the number produced with Moore combined with CBM. While in the case of large tasks, the number produced with the proposed approach is much bigger than the total production using the modified Moore algorithm.

Table 2: Summary of the obtained results

Task size	Method	Machine Utilization (%)	Maintenance (%)	Lost Time (%)	Quantity Produced
Small Tasks	Proposed A.	97.33	0.97	1.7	25244
	MCBM	84.65	1.78	13.57	25349
Medium Tasks	Proposed A.	98.1	1	0.9	26049
	MCBM	87.96	1.7	10.34	26903
Large Tasks	Proposed A.	96.42	1.28	2.3	28025
	MCBM	83	1.72	15.28	25200

The Obtained results are in coherence with the results of the previous subsection. We can conclude that the proposed approach allows us to better manage the health of the machine through controlling what is to produce and with which speed. Although this approach provides good results on the small and medium tasks, it is better to use it in case of large production orders. Finally, it is important to integrate the prognostics information in the scheduling of production in a closed loop style by considering the future loads and how they will effects the system in question.

6 CONCLUSION

In this paper, we presented a new approach in integrating the RUL of a machine in the decision making process. The approach is based on an iterative decision making process where at each step the new evolution of the systems' RUL is considered. The closed loop approach was applied on multiple components in a single machine and was evaluated in terms of cost-benefits. The obtained results were compared to a modified Moore algorithm combined with a classic CBM approach. They show that our approach overpasses classical ones.

As future work, we plan to generalize this approach on the different systems configuration and granularity levels, on one hand. The upgrade from single machine to a multiple machines system is challenging for the computational capacity of the proposed algorithm. On the other hand, the proposed approach has two key decision variables; the duration of the rolling horizon and the duration of the partial decision compared to the rolling horizon. It is in our plans to optimize these variables.

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