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Tactical planning and predictive maintenance: towards an integrated model based on ϵ -reliability

David Lemoine^{1,2} and Bruno Castanier^{3,4}

¹ IMT Atlantique, France

² LS2N, CNRS UMR 6004

david.lemoine@imt-atlantique.fr

³ Angers University, France

⁴ LARIS, CNRS EA7315

bruno.castanier@univ-angers.fr

Abstract. Elaborating some Master Scheduling Programs to maximize the customer product demands in respect to the different logistics costs and optimizing maintenance policies are classically addressed independently by two scientific communities whose interests may in some cases diverge. The objective of this paper is to build, based on recent contributions from the field of maintenance optimization, an integrated optimization approach for tactical production plans and maintenance decisions. This goal of integrating as much information as possible into more holistic approaches and more relevant decisions is clearly one of the challenges that can be found in the precepts of the “Industry of the Future”. In this paper, we propose, through a modeling of the effects of the degradation of the production system on its production efficiency, to show a benefit of the simultaneous consideration of both concerns. Feasibility criteria are also proposed to ensure the robustness of given tactical plans against the hazards of degradation and failure of the production system.

Keywords: Tactical planning · Predictive maintenance · Feasibility criterion · Stochastic Simulation-based approach

1 Introduction

Tactical Production Planning problems are often modelled by so-called “Lot-Sizing” models which are based on an estimated capacity of the production system. This leads to plans that are at best sub-optimised, at worst unfeasible, and many studies have attempted to refine this estimate by taking into account operational constraints, in particular by integrating scheduling constraints [1]. Nevertheless, few researches take into account the impact of the ageing of this system and the loss of capacity caused by maintenance operations, whether preventive or curative. Moreover, when maintenance is considered, it is only seen as a capacity-consuming activity (when maintenance models are based exclusively

on lifetime laws, block or age-based policies can be used to define periodicity constraints that facilitate capacity reservation [2]). Planning maintenance therefore amounts to determining the best compromise between minimising disruption to production and guaranteeing reliable performance at the lowest cost. But, if we consider that ageing performance can vary according to the use and the operations carried out, it is possible to differentiate degradation behaviours according to the items whose production is planned. Thus, we see an interdependence between the two types of planning: maintenance decisions are made according to the planned production as planned production is a function of the maintenance decisions. Thus, just like the production planning process, maintenance planning is also a performance lever for the production system and it makes sense to consider them into an integrated process.

In the search for performance and the associated instrumentation of production tools, conditional type approaches for which the maintenance decision is defined according to a health state estimated with the information collected on the system [3], are based on state indicators (typically the performance level of the system) or prognosis indicators such as the Residual Lifetime (RUL). These indicators allow to define optimality structures for maintenance decision policies. The use of the Residual Lifetime clearly serves as a basis for predictive maintenance whose importance is growing in the context of Industry 4.0. That is why, from [4], we propose a new methodology based on this indicator (more precisely on a reliability threshold estimated over a production period instead of a limit degradation level).

2 Problem modeling

In order to provide feasible production plans, tactical production planning requires a good estimate of production capacities. However, these estimates may vary throughout the planning horizon, especially due to degradation of production resources that may lead to decreases in machine efficiency but also to a range of breakdowns. Thus, in a first part we give a general lot sizing model with finite capacities which allows to obtain different production plans (end items as well as components). It is known to be the classical model which extends material requirements planning (MRP) concept by taking into account production capacities [5]. Then we will detail in a second part the way we model the loss of performance related to the degradation of machines.

2.1 The tactical planning model

The dynamic multi-level capacitated lot-sizing problem (MLCLSP) was introduced in [6]. Here, we detail the formulation given by [7]. Parameters and decision variables of the model are summarized in Table 1.

Table 1. Notations of the MLCLSP

Index sets

\mathcal{N}	: Set of items, $\mathcal{N} = \{1, \dots, N\}$
\mathcal{T}	: Set of periods, $\mathcal{T} = \{1, \dots, T\}$
\mathcal{S}_i	: Set of direct successors of item i in the Bill Of Material (BOM)

Parameters

a_{ij}	: Quantity of item i directly required to produce one unit of item j
C_t	: Available capacity of production system at period t
$D_{i,t}$: External demand of item i at period t
h_i	: Unitary holding cost of item i per unit and period
s_i	: Setup cost of item i
p_i	: Production time per unit of item i
b_i	: Setup time of item i
l_i	: planned lead time for item i

Variables

$X_{i,t}$: Binary setup variable of item i at period t
$Q_{i,t}$: Production quantity of item i at period t
$I_{i,t}$: Inventory of item i at the end of period t

Thus, we can write the model as follows:

$$\text{Minimize } \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{N}} (s_i X_{i,t} + h_i I_{i,t}) \quad (1)$$

s.t.

$$I_{i,t} = I_{i,t-1} + Q_{i,t-l_i} - \sum_{j \in \mathcal{S}_i} a_{ij} Q_{j,t} - D_{i,t} \quad \forall (i, t) \in \mathcal{N} \times \mathcal{T} \quad (2)$$

$$\sum_{i \in \mathcal{N}} (p_i Q_{i,t} + b_i X_{i,t}) \leq C_t \quad \forall (k, t) \in \mathcal{K} \times \mathcal{T} \quad (3)$$

$$Q_{i,t} \leq C_t X_{i,t} \quad \forall (i, t) \in \mathcal{N} \times \mathcal{T} \quad (4)$$

$$Q_{i,t}, I_{i,t} \geq 0 \quad \forall (i, t) \in \mathcal{N} \times \mathcal{T} \quad (5)$$

$$X_{i,t} \in \{0, 1\} \quad \forall (i, t) \in \mathcal{N} \times \mathcal{T} \quad (6)$$

(1) is the logistic costs we seek to minimize. (2) is the inventory balance constraint and (3) is the capacity constraint concerning production and setup time. (4) ensures that production of item i takes place at period t , only if the resource is setup for this item. (5) and (6) are positivity and integrity constraints.

In such a model, it can be seen that p_i , the capacity consumed to produce one item i , is independent of the performance level of production system. The aim of the next section is to explain the way we use to tackle fill this gap.

2.2 Modeling of the performance degradation for production system

Here, we consider that the production system degrades as it is used: this degradation results in a loss of real capacity by increasing operating times. We denote

x_τ the effective performance rate at workload level τ since the last preventive maintenance, which we assume to be measurable for all τ . We also assume that the degradation of this rate is a continuous, workload-dependent, increasing stochastic process and that its expectation is a function of the load induced by the manufactured product (its unit processing time).

More formally, we note $\{X_\tau, \tau > 0\}$ the stochastic process modeling the evolution of the degradation of the performance rate of the production system where τ represents the workload already processed by the production system. We assume that at the new state (X_0) the rate is equal to 1 and that the process is strictly decreasing until 0 (state in which the machine is so degraded that it is not able to produce anymore). We suppose that on an interval $[\tau, \tau + \Delta\tau]$, the loss of performance is modeled by a random variable which follows a Gamma distribution $\Gamma(\alpha\Delta\tau, \beta)$ where α and β were previously estimated. This modelling in the form of a homogeneous gamma process is classical in maintenance [8]. However, as the operating times are particularly low with respect to the planning horizon, we assume in our modeling that the performance rate is constant during the manufacturing of a product unit and that its evolution only occurs at the end of the production of this unit.

As previously mentioned, we also take into account the increase in the duration of the operating times as a function of the level of the performance rate of the system. More precisely, if x_τ represents the performance rate of the production system at the load level τ , we note $p_i(x_\tau)$ the unit production capacity of an item i associated with this rate and we will thus have, for a non-maintained system, $p_i(x_\tau)$ the production capacity of an item i associated with this rate :

$$\begin{aligned} - & x_{\tau+p_i(x_\tau)} < x_\tau, \\ - & p_i(x_{\tau+p_i(x_\tau)}) \geq p_i(x_\tau). \end{aligned}$$

We also take into account the failures (breakdowns) of the production system, failures that we always assume to be cataleptic and requiring corrective maintenance (that takes C_{Corr} units of capacity) to get the system back on line. We assume that these failures are distributed according to a failure rate $\lambda(x)$ which depends on the performance rate of the system. Moreover, we assume that this rate decreases in x . Thus, the lower the performance rate of the system, the higher the probability of failures. Since we have made the assumption that the performance rate is constant during the manufacturing of an item, it will be the same for the failure rate and if the manufacturing of an item i starts at workload level τ , then the expected number of failures during its manufacturing will be $\lambda(x_\tau)p_i(x_\tau)$.

Fig. 1 illustrates the modeling of the performance rate for a given production period, considering the system as new at the beginning of the period. It can be seen from this model that the integration of the system degradation implies taking into account the sequencing of the production lots.

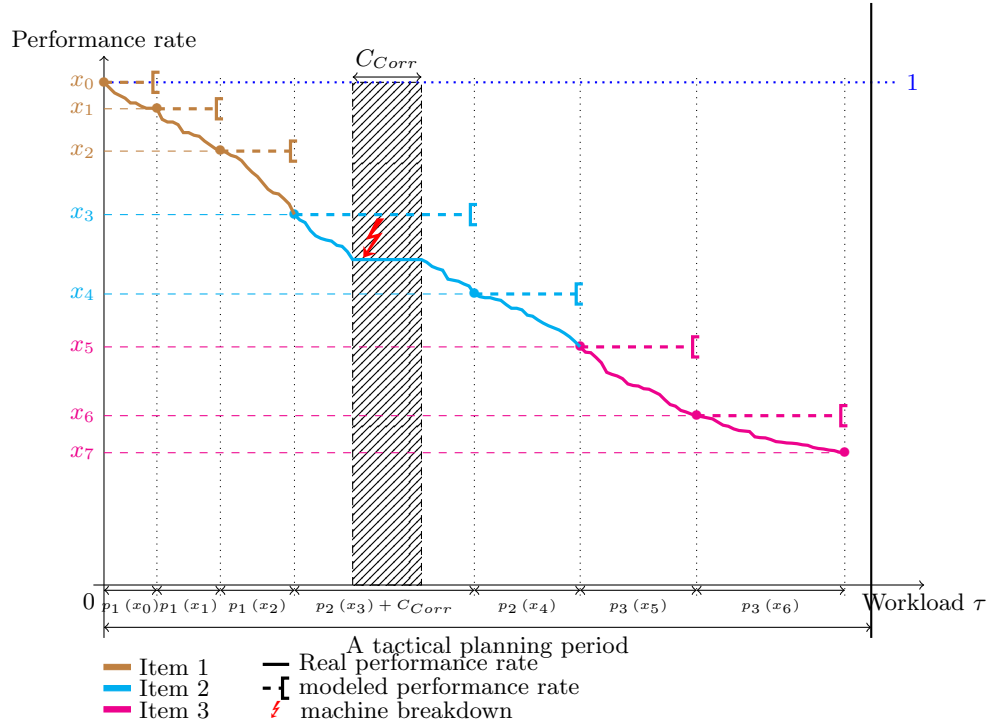


Fig. 1. Example of a scenario of the realization of a production plan according to the evolution of the performance degradation

2.3 The performance indicator: the ε -reliability

In this section, we define a feasibility indicator that ensures the robustness of the production plan with a certain level of probability ε . Based on the ε -feasible indicator provided by [4], we recall the concept of ε -feasibility for one period and we define the ε -reliability indicator on which we base our proposal.

Definition 1 (ε -feasible Period). *A period $t \in [1, T]$ is said to be ε -feasible if and only if the probability of not exceeding the production capacity (taking into account all the capacity consumption, including maintenance) is greater than or equal to ε .*

Using this indicator, [4] qualify a production plan as ε -feasible if all its periods are $\sqrt[\varepsilon]{\varepsilon}$ -feasible. This definition allows them to develop an algorithmic solution based on the simulation of the entire production plan. However, the obligation to have an identical probability of success at each period induces a rigidity that we propose to remove thanks to the ε -reliability

Definition 2 (ε -reliable production plan). *A production plan is called ε -reliable if and only if each production period $t \in [1, T]$ is ε_t -feasible and $\prod_{t=1}^T \varepsilon_t \geq \varepsilon$.*

Indeed, by using such a definition, we allow more flexibility on the distribution of the robustness over the periods of the planning horizon while ensuring the same overall level of robustness of the production plan.

3 Our approach

Conditional maintenance approaches allow maintenance to be organised as best as possible, essentially on the basis of the degradation state of the system itself. A predictive strategy can be seen as conditional maintenance for which the decision variable is usually a residual life. This residual lifetime is characterised by a conditional reliability that is a function of this same state. In [4], authors studied a conditional scheme for which the decision threshold was optimised to guarantee the best compromise between performance rate and available capacity. The maintenance decision can then be made at any time during production, regardless of organisational constraints. Here, we propose to develop a predictive maintenance policy allowing a restoration of the production system according to its state of performance while taking into account the customer's requests translated in the tactical plan. We will consider that this maintenance can be done at most once per period and can be carried out either at the beginning or at the end of the production period, thus joining a number of operational practices.

Our maintenance policy is based on the ε -reliability indicator. Therefore, at the beginning of each period t , this allows us to adjust its ε_t -feasibility according to the previous periods according to the allocation principle defined below.

Definition 3 (Feasibility allocation).

For each period $t \in [1, T]$, we define

$$\varepsilon_t = \sqrt[T-(t-1)]{\varepsilon} \prod_{j=1}^t FR_j(x_{j-1}) \quad (7)$$

where $FR_j(x_j)$ is the probability of achieving the production plan at period j knowing the performance level x_{j-1} of the production system at the end of manufacturing in precedent period.

Thus, we propose to define a predictive maintenance strategy based on the estimation of the ability of the system to achieve its production plan at each period. The maintenance decision is no longer defined on the basis of lifetime or calendar parameters but is a function of the current state of the system estimated after the production of each item. Even if its implementation in an operational context is more difficult than traditional approaches, these predictive approaches,

which are similar to conditional maintenance under certain assumption, offer real potential for improving performance, particularly in economic point of view [9].

Then, our methodology can be summarized into five iterative steps :

- Step 1 : The datas are readen and the lot-sizing model is initialized with the estimated production capacities C_t for each period t . The effective performance rate for the production system at the beginning is x_0 .
- Step 2 : Thanks to the lot-sizing model, an optimal production plan is elaborated (by using, for instance, a mixed integer linear program or an optimization method), $t \leftarrow 1$.
- Step 3 :
1. ε_t is computed thanks to the feasibility-allocation formula (7)
 2. The production plan is simulated at period t according to the performance rate x_{t-1} (the performance rate at the beginning of period t). The probability of achieving the production plan at period t $FR_t(x_{t-1})$ is then computed.
 3. if $FR_t(x_{t-1}) \geq \varepsilon_t$ then go to Step 4 else
 - * if there is no preventive maintenance at the beginning of period t , schedule one: $x_{t-1} = 1$. Go back to 2.
 - * if there is a preventive maintenance at the beginning of period t , C_t is the decreased and the lot-sizing model is updated. Got to Step 2.
- Step 4 : x_t is computed as the the median of all observed performance rates at the end of period t thank to the simulation model. $t \leftarrow t + 1$. Go to Step 5
- Step 5 : If $t = T + 1$ then Stop (a feasible plan has been elaborated) else go to Step 3.

At each period t , in the simulation process two kinds of maintenance are considered:

- If a failure occurs, minimal corrective maintenance (with no effect on the performance rate of the production system) is performed (in this case a capacity consumption corresponding to the maintenance time) and a corrective maintenance cost is added.
- If a preventive maintenance occurs, then a capacity consumption corresponding to the maintenance preventive is taken into account and a preventive maintenance cost is added.

Fig. 2 sketches our methodology.

4 A software tool

To improve the applicability of our approach in an industrial context or at least to get their feeling, the algorithm is directly implemented in a computer program with an ergonomic and user-friendly interface. The final results are numerically and graphically presented.

This interface is divided into four modules:

1. a data management module for loading, saving or importing data from an external database;

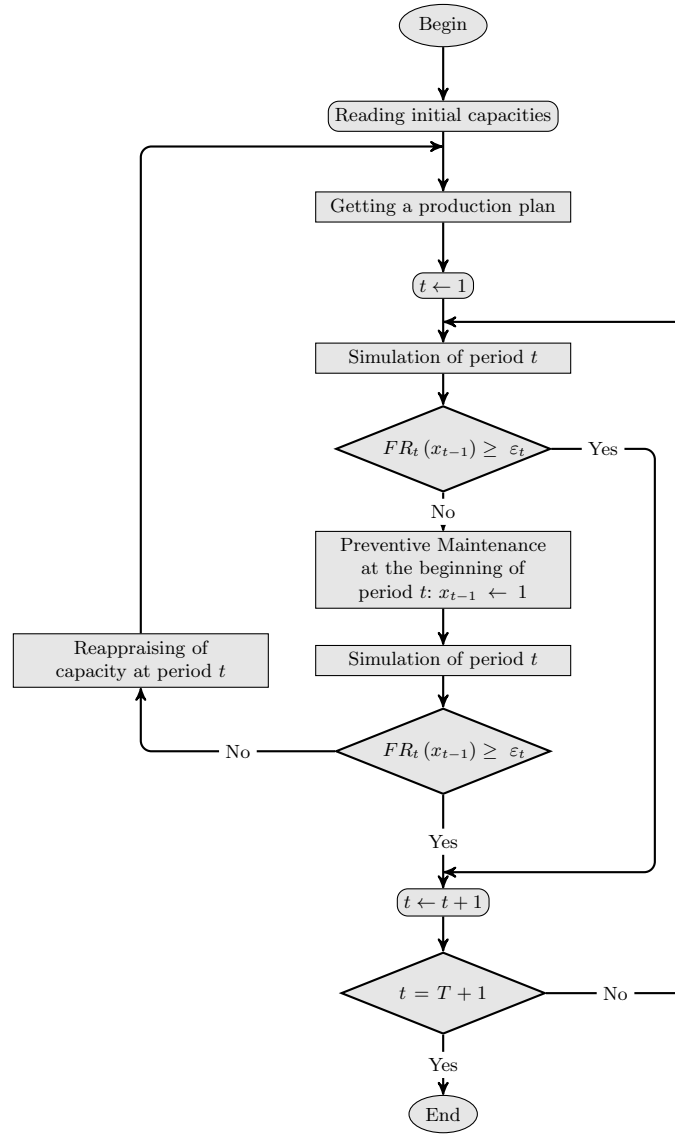


Fig. 2. Optimization scheme for the considered predictive maintenance policy

2. a tactical planning process module for building and optimising the mathematical model based on instances using, for instance, the Cplex solver;
3. a simulation module for estimating the feasibility of production plans;
4. a graphical interface for the specification of the problem with all the parameters (capacities, costs, degradation, etc.), the presentation of the intermedi-

ate results obtained during the optimisation procedure and the final solution through different graphs presenting the associated indicators (Fig. 3).

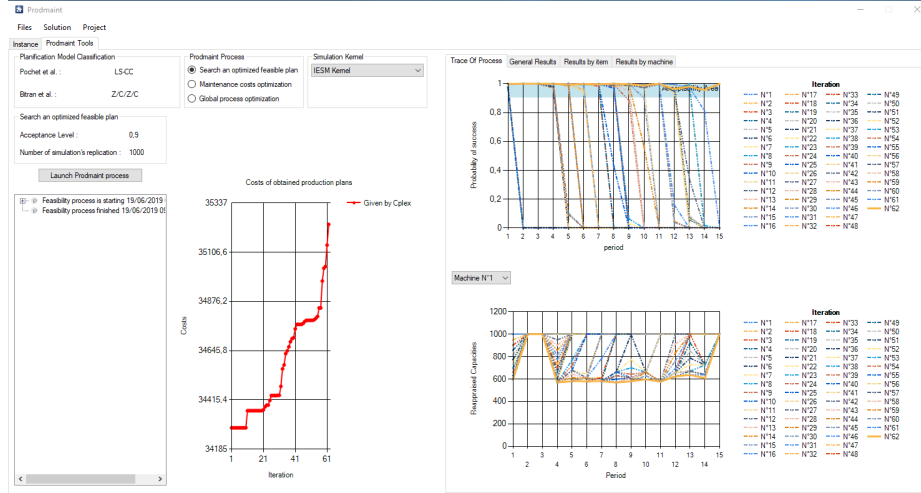


Fig. 3. The GUI of the planning tool

5 Conclusion and further research

In this paper, a new methodology for integrating tactical planning and maintenance has been presented. Using a model of the performance level of the production system thanks to degradation or ageing of the production system on the capacity consumed for manufacturing, and based on a new indicator called ε -reliability, an original maintenance strategy, based on considerations developed in a predictive maintenance context, has been proposed. A Feasibility-Allocation process has been designed in order to ensure a certain robustness level for elaborated tactical plans. Thus, our model extends classical approaches combining production and maintenance essentially focused on the unavailability times generated by preventive maintenance, with a stronger contribution on the interaction between the system degradation and its productivity. This has been integrated into a demonstration software platform for industrial purposes.

The model presented opens up many areas of development for future work in both the modelling and optimisation fields. One of the first points that would be interesting to address is the possibility of modulating the maintenance decision rules in order to offer the possibility of an optimised positioning of preventive maintenance according to opportunities linked, for example, to changes in series time or others. As we pointed out that scheduling has an impact on the performance level of the production system, integrating sequencing decision on the

manufacturing of each production lot could be an interesting area of improvement. Another perspective of research could be to develop a model for which the preventive maintenance decision is not restricted to a total recovery of performance but to define the effectiveness of the operation to be implemented according to the capacities not consumed by the production plans, the effectiveness being able to be correlated with an effective maintenance time. On the field of optimisation and more precisely on the criteria to be taken into account, even if the feasibility partially captures the volatility of the global planning problem, it could be interesting to extend the average maintenance criteria.

References

1. Dauzère-Péres, S., Lasserre, J.B.: Integration of lotsizing and scheduling decisions in a job-shop. *European Journal of Operational Research* **75**(2), pp. 413–426 (1994)
2. Pandey, D., Kulkarny, M. S., Vrat, P.: A methodology for joint optimization for maintenance planning, process quality and production scheduling. *Computers & Industrial Engineering*, **61**(4), pp. 1098–1106 (2011)
3. Jafari, L., Makis, V.: Joint optimal lot sizing and preventive maintenance policy for a production facility subject to condition monitoring. *International Journal of Production Economics*, **169**(C), pp. 156–168 (2015)
4. Castanier, B., Lemoine, D.: A Preliminary Integrated Model for Optimizing Tactical Production Planning and Condition-Based Maintenance. In: *Industrial Engineering and Systems Management - IESM 2011*, pp. 998–1007. Metz, France (2011)
5. Comelli, M., Gourgand, M., Lemoine, D.: A review of tactical planning models. *Journal of Systems Science and Systems Engineering*, **17**(2), pp. 204–229 (2006)
6. Billington, P. J., McClain, J. O., Thomas, L. J.: Mathematical Programming Approaches to Capacity-Constrained MRP Systems: Review, Formulation and Problem Reduction, *Management Science*, **29**(10), pp.1126–1141 (1983)
7. Buschkühl, L., Sahling, F., Helber, S., Tempelmeier, H. Dynamic capacitated lot-sizing problems: a classification and review of solution approaches. *OR Spectrum* **32**, pp. 231–261 (2010).
8. Van Noortwijk, J.M.: A survey of the application of gamma processes in maintenance. *Reliability Engineering & System Safety*, **94**, pp. 2–21 (2009)
9. Castanier, B., Béranger, C., Grall, A. A Sequential Condition-Based Repair/Replacement Policy with Non Periodic Inspections for a System subject to Continuous Wear. *Applied Stochastic Models in Business and Industry*, **19**, pp. 327–347 (2003)