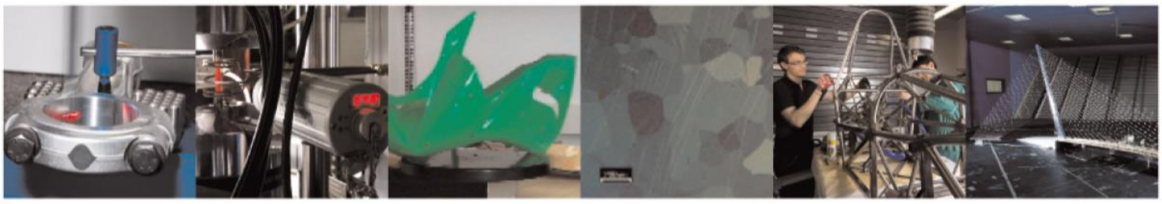

Impact of condition based maintenance policies on the service level of multi-stage manufacturing systems

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Impact of Degradation Based Maintenance Policies on the Service Level of Manufacturing Systems

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Abstract

Preventive maintenance is crucial for keeping the operational condition of machines but it affects the available productive time of the system. This influences the lot completion time and the delivery dates. Therefore the choice of preventive maintenance policies needs to be taken by jointly considering the actual condition of machines and the service level of the system. In this context, the main contribution of this paper consists in providing evidences of how the completion time of a lot is significantly affected by the preventive maintenance policy. This is done by means of numerical illustrations obtained by using both ad-hoc models and a real industrial case. The second contribution relies in the presented methodology that allows the modeling of general synchronous production lines and, given a lot size, the computation of their corresponding service level. The methodology is described in such a way that its extension to different scenarios (such as different system layout and asynchronous machines) is fairly straightforward.

Key words: Manufacturing systems, Performance evaluation, Preventive Maintenance, Degrading Machines

1. Introduction

Manufacturing systems consist of processing machines, material handling and other equipment that gradually deteriorate and are subject to failures during operations. The occurrence of unplanned breakdowns can lead to costly corrective repairs, which can negatively impact the available production time of the system [1]. Therefore, in order to avoid producing in unsafe degradation states that can lead to catastrophic failures, manufacturers carry out planned preventive maintenance of critical production resources [2]. On the other hand, current market trends characterized by highly customized products and shorter delivery times push manufacturers to increasingly compete under a Make to Order strategy and require to guarantee a higher equipment availability [3]. However, performing preventive maintenance requires machines to be temporarily stopped [4], thus causing planned down times. Although down times associated to preventive maintenance are normally shorter and incur lower costs compared to corrective repairs, very frequent preventive maintenance can also lead to an overall decrease in the operational availability of production systems [5]. Hence, effective maintenance planning, supported with appropriate decision making tools is one of the essential activities to achieve high productivity and cost efficiency in complex manufacturing systems [6]. In order to achieve this goal, the decisions related to preventive maintenance need to consider actual degradation level of machines, the downtimes associated to alternative maintenance actions and the desired availability of resources for satisfying existing customer due dates[7]. Indeed, a robust maintenance and production planning is one of the competitive strategies for meeting key customer requirements such as production completion dates and product quality while preserving the condition of high value processing equipment.

1.1. Industrial Motivations

Manufacturing industries with heavy investment on production equipment spend a significant portion of their operating budget on maintenance. According to [8], maintenance costs can account for 15-70% of the total production costs. Therefore, one of the industrial challenges to implement an efficient maintenance policy which is adapted for a specific manufacturing setting is the evaluation of the impacts of alternative policies on costs and other key performance indicators affected by maintenance decisions [9], [10]. For this reason, manufacturing systems composed of many production equipment require an overall system level analysis.

In manufacturing, maintenance policies can be viewed into two main groups, namely corrective maintenance(CM) and preventive maintenance (PM) [11]. Preventive maintenance consists of actions carried out based on a plan to keep an equipment within a stated working condition through the process of checking, reconditioning and replacing [12]. PM can be further classified into Time-Based maintenance (TBM), where maintenance is performed at certain time intervals, or condition-based maintenance (CBM), where maintenance is performed when the state of the machine reaches a specific degradation conditions that require a repair [13]. In particular, the system level impacts of condition based maintenance and the specification of its corresponding parameters needs to be studied using accurate and robust quantitative decision support tools. However, surveys show that current industrial practices highly rely on decisions based on experience, thus, maintenance decision support tools are not commonly applied at a system level[14].

The choice of maintenance policies is mainly driven by target performances, such as overall equipment availability, costs and the feasibility of enabling technologies [15]. Thus, advances in sensor and monitoring technologies have been one of the major factors influencing industrial trends and their choice of maintenance policies. A survey conducted in 2010, including more than 170 Italian manufacturers investigated the average mix of maintenance policies that were adopted by the companies. In this study, on average, the companies applied

55% of CM, 35% TBM and 10% CBM, for their identified reliability problems. However, the same study recommended 30% of CM and 70% of combined TBM and CBM [16] to obtain optimal results. Furthermore, the compound annual growth rate for the CBM is estimated to be 39% in the period 2017 to 2022 [17]. Additional studies also forecast a growing shift from CM to CBM due to the economic feasibility of advanced condition monitoring technologies and powerful data analytics tools. However, besides the average industrial trend, the choice of maintenance policies and the specification of maintenance parameters needs to be considered depending on the nature of the individual equipment and the manufacturing system layout. In this regard, manufacturing system layout, which governs the production flow in a system, is highly influenced by the nature of maintenance operations. Accordingly, research has investigated the interaction between maintenance activities and production logistics, demonstrating the economic benefits that can be achieved by triggering maintenance considering production inventory conditions and choosing opportunistic time windows [18]. Thus, joint maintenance and production logistics analysis tools for supporting decision making can bring significant performance improvements for industries [19].

Once the required decision support tools are developed, the implementation of condition based maintenance is also dependent on the availability of enabling information communication technologies (ICT) used for component condition monitoring [17]. The quantitative models which are embedded in the decision support tools elaborate the condition monitoring information at component level and the production logistic data coming from manufacturing executive systems, in order to evaluate the performance of alternative set of maintenance and control actions[20], [21]. For this purpose, a suitable condition monitoring system, where signals are continuously gathered using sensor networks is needed to provide the information about health assessment of critical components [22], [23]. The information gathered through such a framework is used to make inference on various process monitoring variables, such as vibration, temperature, power consumption, and acoustic emissions or on multi-sensor data fusion [24]. However, in today's manufacturing systems, ICT platforms for supporting data connectivity and computations are increasingly becoming integral part of modern production systems. This trend in the digital manufacturing is introducing the concept of Cyber Physical Systems (CPS), which are defined as integrations of computation and physical processes [25]. This provides an additional opportunity to exploit the synergy between CPS enabled industries and embedded decision support tools. The method proposed in this paper belongs to these class of tools within the decision support system, which jointly considers condition based maintenance and production plans.

1.2. Literature

In reliability engineering and maintenance policy analysis, various modeling approaches and quantitative solution methods have been proposed. In the literature, modeling approaches such as, Markov chain models [26], [27], [28], Petri nets [29],[30] Reliability Block diagrams [31],[32], Fault Tree Analysis

[33],[34] and Analytic Hierarchy Process[8] are well investigated. Each of these approaches have their own specific advantages depending on the modeling objectives [35]. Some of the criteria in selecting an approach include, the required modeling resolution, size and complexity of the model, flexibility and generality, analytical tractability, computational effort [36]. For instance, Markov chain based approaches are powerful for modeling and studying the steady state and transient behavior of state based stochastic systems. On the other hand, Petri net based approaches are suitable for component and system fault verification, diagnosis, detection of undesired states and support subsequent design of control and supervision systems. Reliability Block Diagrams and Fault Trees are suitable to provide an intuitive representation in modeling reliability problems and give a higher expression power to demonstrate how a component failure contributes to the failure of complex system. Multi criteria decision making tools such as Analytic Hierarchy Process allow to incorporate experience based inputs by considering multiple objectives, in addition to maintenance policy analysis [37]. Furthermore, there are other works based on hybrid use of two or more of these approaches [38], [39] with the objective of combining the advantages of the individual approaches.

In addition to the modeling approaches, commonly used quantitative solution methods can be based on exact and approximate analytical methods, simulation methods and heuristic methods. Each method can present specific advantages and limitations. Simulation methods are suitable for modeling a wide range of manufacturing system architectures and provide accurate estimation of performance measures [40]. However, creating simulation models of multi-stage manufacturing lines and the subsequent simulation time can be too high for short term decision applications [41], [42]. In such cases, approximate analytical methods represent a suitable alternative to simulation when estimating the performance of complex manufacturing systems in a short time. They are accurate and fast in the estimation of the main performance measures. This allows the evaluation of a large set of system alternatives and parameter settings in a short time. The work presented in this paper is also grounded on a growing body of research that is based on Markov chain based analytical methods. Such early models dealt with the analysis of serial transfer lines [26] and asynchronous flow lines [43], with single failure mode machines. Later, these methods were extended to deal with more complex machine models, featuring multiple failure modes [44]. Recently, methods for studying complex system layouts [45] have been proposed. These works have been foundation for the development of various decision support system for the design and management of complex manufacturing systems [46], [47]. Although these works bring significant advancement in this area, they do not take into account the degradation dynamics of machines. Therefore, the main goal of this paper is also to extend their applicability for supporting a more detailed maintenance decision.

Traditionally, the research on the decision support tools in maintenance of manufacturing systems considers the analysis of condition based maintenance and the analysis of production logistics performances separately. In recent years, works focusing on the joint preventive maintenance and production performance optimization are attracting researchers and industrial interests. A review of such works [18] presents the growing interest and the motivation behind the joint analysis of preventive maintenance and production logistics problem while also indicating that fewer works have embedded the condition based maintenance in the analysis. Among these works covering condition based preventive maintenance policies, many of them analyze and optimize the problem at single stage level [48], [49],[50],[51], thus neglecting their impact on the production logistics performance of the multi-stage system as a whole. Other works show that the impact of alternative maintenance policies taken on individual machines can be very different from its impact on the performance of the overall system, which affects the productive time and the completion times of the customer orders. Recent research is also targeting the systemic aspect of the problem, highlighting that single stage level analysis undermines the efficiency of the condition based maintenance policies on the whole system, by prioritizing local improvement actions which might be detrimental at system level [52].

With a similar goal of addressing the maintenance problem at a system level, the research in opportunistic maintenance aims to optimally group repair operations [53], [54] and develop methods to schedule maintenances considering less disruptive opportunities,[55], [56], [57]. Detailed classification of these approaches and the performance measures targeted by works in this area are reviewed in [58]. On the other hand, works focusing on the production performance modeling and analysis of multi-stage manufacturing systems mainly consider simplified assumptions of machine reliability parameters. Mainly, these works consider machine failure parameters as the average values of mean time to failures (MTTF), without the explicit representation of the machines' degradation dynamics.

The importance of a decision making process by jointly considering condition based maintenance and production logistics performance has been recently stressed in [46]. In [59] the authors developed a model of a multi-stage asynchronous serial line where machines are subject to deterioration. While going through deteriorated states, increasing failure rate and decreasing yield are observed. The authors have demonstrated that in multi-stage systems, while selecting the optimal maintenance thresholds, the solutions obtained by neglecting the system dynamics are always sub performing in terms of effective production rate and always overestimate the length of maintenance cycles. These recent works are mainly focused on the analysis of the interaction among preventive maintenance policies and first order performance measures of the system, such as the average system throughput and the average work in progress. If properly controlled, preventive maintenance operations can potentially reduce the variance of the output, thus increasing the service level, paving the way to a robust joint maintenance and production planning approach.

1.3. Scope of the paper

The primary objective of this paper is to show how preventive maintenance affects the time to completion of a lot. We provide insights on this fairly new research area by means of experiments are that are divided in two parts: the first that takes in consideration three simple ad-hoc models and studies the behavior of their time to complete a lot as function of different parameters; and the second part that focuses a real Flexible Manufacturing System (FMS) for the production of complex titanium parts in the aeronautic sector.

All the underlying models used in the experiments are synchronous production lines composed of two machines connected by a buffer controlled by a blocking before service policy. Only one of the machines of these models is always characterized by a degrading component that is subject to both corrective and preventive maintenance. Indeed, this is only one of many possible scenarios since many different modeling assumptions exist (see [60] for a detailed list). For the sake of brevity, we have chosen the model whose assumptions were the best fit for the real use case.

Despite this, we describe in detail a methodology that holds for:

- production lines composed of an arbitrary number of machines connected by buffers having arbitrary sizes;
- machines with general behavior.

Furthermore, the method for the computation of the lot completion time can be applied to any type of system layout as long as it is possible to generate the underlying DTMC of the model and discriminate the states of the machine that generates the output of the system. This is straightforward for closed loop systems and assembly line (see [61] where a similar method has been defined for the computation of the lead-time distribution).

Additionally, the method can be easily adapted to deal with asynchronous machines. In this case the underlying stochastic process corresponds to a *Continuous Time Markov Chain* (*CTMC*) instead of a *Discrete Time Markov Chain* (*DTMC*). Therefore, the state transitions become more complex because their computation involves a matrix exponentiation but the structure of the matrices and the recursive schema of the method remains unchanged. We refer the reader to [62] for a description of how manage the transitions in a CTMC and to [63] for a description of general asynchronous machines by using Kronecker products in a continuous time setting. To the best of our knowledge, the method can be easily adapted to any system with a discrete state space. For these reasons, we believe that the methodology can be adapted to cover a large set of systems and its extension to different scenarios is straightforward.

The paper is structured as follows: in Section 2, the modeling assumptions are introduced. In Section 3, the methodology for modeling degrading machines is described and the analytical method for evaluating the target performance measures of the system is presented. Section 4 presents numerical results of the impact of condition based preventive maintenance of degrading machines on the system performance measures. In addition, this section includes a real case study analysis and the resulting system behavior. Conclusions are given in Section 5.

2. System Modeling

2.1. Main Modeling Assumptions

The proposed methodology can be applied to any manufacturing line with multiple number of stages. The typical serial manufacturing line is composed of K unreliable and degrading machines separated by $K-1$ limited capacity buffers, as represented in 1. The machines (squares) perform operations on parts flowing in the system. Buffers (circles) have the role of decoupling the machines in the system. They can be either inventory storages or automated material handling systems that transport semi-finished materials between machines. The i^{th} machine and buffer are denoted with M_i and B_i (with $i = 1,, K-1, K$) respectively: B_i has capacity equal to N_i and it contains only pieces already worked by M_i. A generic M_i is blocked if the downstream B_i is full. A generic M_i is starved if the upstream dedicated buffer B_{i-1} is empty. The first machine is never starved, meaning that there is continuous supply of raw parts at machine M_1, and the last machine is never blocked, meaning that there is always place to store finished products.

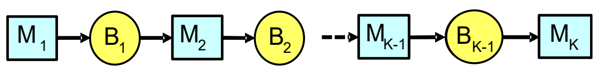

Figure 1: Representation of multi-stage serial manufacturing line

The underlying DTMC of the model can be built by iterating the construction of a system composed of two machines connected by a buffer (building block from now-on). The flow of material in a building block is modeled as a discrete flow of parts. Each machine M_i, $i = 1, 2$, is characterized by a set of states S_i with dimensionality N_i. The dynamics of each machine in these states is captured in the transition probability matrix T_i that is a N_ixN_i matrix. Moreover, a quantity reward vector μ_i is considered, with dimensionality N_i and binary entries: $\mu_i^j = 1$ if the machine is operational and it processes 1 part per time unit while in state j; $\mu_i^j = 0$ if the machine is down and it does not process parts in state j. The generic state indicator for this system assumes the form $s = (b, \alpha_1, \alpha_2)$, where b is the number of parts in the buffer and α_i assumes values in the set S_i . In total $(B+1) \times N_1 \times N_2$ states exist. For each machine, the states are partitioned into up states (the machine is operational), denoted as U, and down states (the machine is not operational), denoted as D. Because of such partitioning, the transition probability matrix of M_i, denoted with T_i, can be divided into blocks as follows

$$T_i = \begin{vmatrix} \bar{P}_i & P_i \\ R_i & \bar{R}_i \end{vmatrix} \tag{1}$$

where, considering machine i, the block $\bar{P}_i$ contains the transition probabilities among the up states, $\bar{R}_i$ among the down states, P_i from up states to the down

$$
Q = \begin{array}{c|cccccccc}
 & 0,D,U & 1,U,U & 1,D,U & 1,D,D & 2,U,U & 2,U,D & 2,D,U & 2,D,D \cdots \\
\hline
0,D,U & \bar{R}_1 \otimes I & R_1 \otimes I & & & & & & \\
1,U,U & P_1 \otimes \bar{P}_2 & \bar{P}_1 \otimes \bar{P}_2 & & P_1 \otimes P_2 & & \bar{P}_1 \otimes P_2 & & \\
1,D,U & \bar{R}_1 \otimes \bar{P}_2 & R_1 \otimes \bar{P}_2 & & \bar{R}_1 \otimes P_2 & & R_1 \otimes P_2 & & \\
1,D,D & \bar{R}_1 \otimes R_2 & R_1 \otimes R_2 & & \bar{R}_1 \otimes \bar{R}_2 & & R_1 \otimes \bar{R}_2 & & \\
2,U,U & & & P_1 \otimes \bar{P}_2 & & \bar{P}_1 \otimes \bar{P}_2 & & & P_1 \otimes P_2 \\
2,U,D & & & P_1 \otimes R_2 & & \bar{P}_1 \otimes R_2 & & & P_1 \otimes \bar{R}_2 \\
2,D,U & & & \bar{R}_1 \otimes \bar{P}_2 & & R_1 \otimes \bar{P}_2 & & & \bar{R}_1 \otimes P_2 \\
2,D,D & & & \bar{R}_1 \otimes R_2 & & R_1 \otimes R_2 & & & \bar{R}_1 \otimes \bar{R}_2 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots
\end{array}
$$

Table 1: Upper left corner of the transition matrix of the DTMC of a building block with general Markovian machines.

states (leading to a break down) and R_i from down states to up states (leading to repair).

We further assume that, in each time slot, the state of the machine is determined at the beginning of the time unit and the buffer content is changed accordingly at the end of the time unit. Operational Dependent Transitions are assumed, i.e. a machine cannot make transitions to other states if it is starved or blocked. The Blocking Before Service (BBS) mechanism is assumed. Therefore, when a buffer is full (empty) its upstream (downstream) machine is blocked (starved) and it can only be in the up state. This means that states $(B-1, D, U)$ and $(1, U, D)$ are transient states. The transition matrix of DTMC associated with the system, denoted with Q, can be built by blocks by using Kronecker products. In order to give an example, we provide Table 1 which describes the upper left corner of the transition matrix. The symbol $\otimes$ denotes the Kronecker product operator which is used in this context to describe the parallel evolution of the two machines. Let us discuss just two blocks of Table 1 in detail. The block that contains the transitions that lead from the states in $(1, D, D)$ to the states in $(0, D, U)$ is given by $\bar{R}_1 \otimes R_2$ because if the first machine remains down (described by $\bar{R}_1$) and the second machine gets repaired (R_2) then the buffer becomes empty. The block that provides the transitions from $(0, D, U)$ to $(1, U, U)$ is given by $R_1 \otimes I$, because in this case the first machine gets repaired (R_1) and the second machine maintains its up state (I) since it is starved.

The extension to K machines can be carried on recursively. Let $M_i *_B M_j$ be a binary operator that creates the transition matrix of a building block (as described in Table 1) by using the description of machines i and j and a buffer having capacity B. Furthermore, let us denote the transition matrix representing the dynamics of the first i machines of the line with $Q^{[i]}$. It is easy to verify that $Q^{[2]} = M_1 *_{B_1} M_2$. By separating the states in which the downstream machine of the building block is processing items from those in which it is starved or down, we can partition the matrix $Q^{[2]}$ in order to satisfy equation (1) and create a reward vector $\tilde{\mu}_2$ for the entire building block. By doing this, we define a meta-machine $\tilde{M}_2$ whose output corresponds to the output of M_1 and M_2 as taken in isolation. As defined, $\tilde{M}_2$ can be combined with M_3 to generate $Q^{([3])}$. By induction we have that:

$$Q^{[i]} = \begin{cases} M_1 *_{B_1} M_2 & i = 2 \\ \tilde{M}_{i-1} *_{B_{i-1}} M_i & i > 2 \end{cases}$$

Matrix $Q^{[i]}$ can be partitioned according to equation (1) by filtering the matrix according to the state of the last machine of the building block. Formally:

$$\begin{aligned} \bar{P}_i &= F^{(M_i=UP\ \wedge\ b_i>0)} Q^{[i]} F^{(M_i=UP\ \wedge\ b_i>0)} \\ P_i &= F^{(M_i=UP\ \wedge\ b_i>0)} Q^{[i]} F^{(M_i=DOWN\ \vee\ b_i=0)} \\ \bar{R}_i &= F^{(M_i=DOWN\ \vee\ b_i=0)} Q^{[i]} F^{(M_i=DOWN\ \vee\ b_i=0)} \\ R_i &= F^{(M_i=DOWN\ \vee\ b_i=0)} Q^{[i]} F^{(M_i=UP\ \wedge\ b_i>0)} \end{aligned} \tag{2}$$

where $F^{<cond>}$ is a filtering matrix whose entries are defined as follows:

$$f_{i,j}^{<cond>} = \begin{cases} 1 & i = j \wedge \ <cond> \ \textit{is true in } i \\ 0 & \text{otherwise} \end{cases}$$

The reward vector $\tilde{\mu}_i$ follows the same principle and is equal to:

$$\tilde{\mu}_i = \mathbf{1} F^{(M_i=UP\ \wedge\ b_i>0)}$$

where $\mathbf{1}$ is a vector of ones having the same dimension of the filtering matrix.

As last, it is important to point out that more elegant strategies based on formal methods can be used to generate the state space of large complext multistage systems and enhance the corresponding Markov process with general PH distributions. Above all, we suggest some works based on Stochastic Petri nets [64, 63, 65].

2.2. Modeling of a single machine as superposition of components

Each machine can be described as a superposition of independent components having their own failure and repair probabilities. This makes easier to plug Phase Type (PH) distributions in the dynamics of each component. We remind the reader to [66, 67] for a detailed description about the use of PH distribution in reliability modeling.

Let us assume that a machine i is composed of W_i components and that the j component of M_i is described by a proper DTMC whose matrix is denoted with $T_{i,y}$, and a reward vector $\mu_{i,y}$. Then, the overall behavior of M_i is described by matrix

$$T_i = \bigotimes_{y=1}^{W_i} T_{i,y} \tag{3}$$

and the reward vector $\mu_i = \bigotimes_{y=1}^{W_i} \mu_{i,y}$.

Each matrix $T_{i,y}$ must represent a DTMC but it can be arbitrarily complex having multiple up and down states having general Markovian distributions. Therefore the assumption of independence between components is not restrictive. In fact, the dynamics of components that depends on each other can be represented through a single matrix that describes their combined behaviour.

For example of how PH distribution can be used, assume component y as having failures characterized by a order-2 hyper-geometric distribution and two failure modes both with hypo-geometric time to repair; then, the transition matrix is

$$\begin{vmatrix} 1-p_{i,1} & 0 & p_{i,1}a_{i,1} & 0 & p_{i,1}(1-a_{i,1}) & 0 \\ 0 & 1-p_{i,2} & p_{i,2}a_{i,1} & 0 & p_{i,2}(1-a_{i,1}) & 0 \\ 0 & 0 & 1-r_{i,1} & r_{i,1} & 0 & 0 \\ r_{i,1}b_{i,1} & r_{i,1}(1-b_{i,1}) & 0 & 1-r_{i,1} & 0 & 0 \\ 0 & 0 & 0 & 0 & 1-r_{i,2} & r_{i,2} \\ r_{i,2}b_{i,1} & r_{i,2}(1-b_{i,1}) & 0 & 0 & 0 & 1-r_{i,2} \end{vmatrix}$$

where $b_{i,1}$ gives the initial probabilities of the hyper-geometric times to failure and $p_{i,1}$ with $p_{i,2}$ the parameters of the involved geometric distributions; $a_{i,1}$ is the probability of failure mode 1; $r_{i,1}$ and $r_{i,2}$ are the parameters of the hypo-geometric times to repair.

2.3. Modeling of a Degrading component with CBM

In this paragraph, the general machine modeling framework introduced in the previous section is used to capture the behavior of unreliable components going through progressive degradation states. Degradation is a progressive process that increases the probability of breakdown over time and it is due to the wear of tools, fixtures, etc... The degradation states of the machine are partially observable and inference might be needed. Therefore, the representation of a degradation process might be complex. In sake of clarity we will focus on a monodimensional process. However, it is important to point-out that our method supports any degradation process that can be represented with DTMC.

The sketch of the state-transition diagram for degrading components is represented in Figure 2, where states $l = 1, 2, .., L$ denote the operational states and state CM denotes the breakdown state, where corrective maintenance is required to bring the component back to as good as new condition. In practice, these states may correspond to specific physical component or tool conditions, or they can represent a discretization of the deterioration process, modeled by using PH distributions.

When the component is in the operational state $l = 1, 2, .., L$ it processes $\mu^l = 1$ parts per time unit. The breakdown state is simply characterized by $\mu^{CM} = 0$. In the maintenance literature, it is typical to assume Increasing Failure Rates (IFR). In this paper, IFR can be included by assigning failure probabilities $p_{l_1} > p_l$ for each state $l_1 > l$. If the breakdown occurs, corrective maintenance is needed. The mean time to repair the component is $1/r_{CM}$. The goal of a degradation control policy is to keep the process in desired states by activating preventive maintenance, whenever the component is detected to be in an undesired state, characterized by degraded performance. In our framework, states $l = 1, .., L-1$ are desired states, and state L is the undesired state where a further degradation activates preventive maintenance. The selection of the undesired state threshold L is typically a decision variable of the control policy. Since PM entails less severe repair operations than CM (repair probability

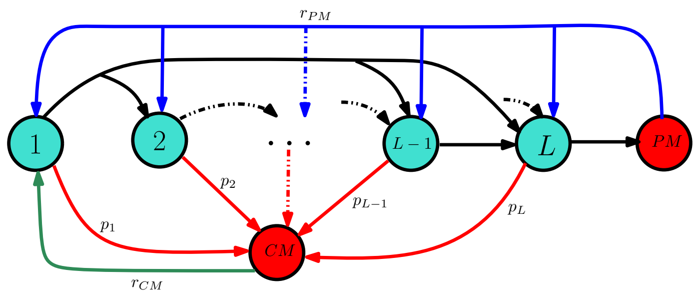

Figure 2: General state-transition diagram of a degrading machine. Black arcs represents degradations, Red arcs represents failures, Green arcs represents recovery from failures and Blue arcs represents recovery from preventive maintenance. Note that, in sake of readability, not all the arcs have been depicted; dashed lines are used to underline the missing transitions.

$r_{PM} > r_{CM}$) this strategy may increase the production rate of the degrading station. After preventive maintenance may or not return to the lowest degradation level.

Figure 2 depicts a degradation that is monodimensional. As a consequence, there is no point in considering more than one threshold L. Nonetheless, our method allows the user to consider multi-dimensional tresholds. In general, our model remain feasible for any kind of degradation and policy that is based on a discrete state space. The analysis of these complex scenarios is left as future work.

2.4. Performance Measures

The main performance measures of interest for this set of systems are:

- Lot completion time, $C(x)$, that is the time to complete a lot of x parts.
- Service level, $SL(x,t)$, which is defined as:

$$SL(x,t) = Prob(C(x) \leq t)$$

3. Performance Evaluation Method

In this section, we describe in details the calculations required to compute the distribution of the amount of time necessary to produce a given lot x, namely *completion time*. Formally, the completion time is defined as:

$$C(x) = min\left[n \geq 0 : Z(n) = x\right] \tag{4}$$

where $Z(n)$ is a random variable corresponding to the number of items processed after n time units. By denoting with X the state of the system, the quantity characterizing the completion time is

$$G_{i,j}(n,x) = \{X(C(x)) = j, C(x) = n | X(0) = i\}$$

which corresponds to the joint probability of the completion time and the system state at completion supposing that the initial state is i. The measure $G_{i,j}(n,t)$ is conveniently described by a pure birth process whose probability matrix, denoted with A, is absorbing and characterized by blocks of states having dimension equal to Q. The structure of the matrix is level-dependent as follows:

$$A = \begin{array}{c|ccccccc} & 0 & 1 & 2 & \cdots & x-2 & x-1 & x \\ \hline 0 & \bar{H} & H & 0 & \cdots & 0 & 0 & 0 \\ 1 & 0 & \bar{H} & H & \cdots & 0 & 0 & 0 \\ 2 & 0 & 0 & \bar{H} & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ x-2 & 0 & 0 & 0 & \cdots & \bar{H} & H & 0 \\ x-1 & 0 & 0 & 0 & \cdots & 0 & \bar{H} & H \\ x & 0 & 0 & 0 & \cdots & 0 & 0 & I \end{array} \tag{5}$$

where:

- H contains only those transitions that brings an item outside the system.
- $\bar{H}$ contains all the remaining transitions of the system in such a way that the relation $\bar{H} = Q - H$ holds.
- I corresponds the identity matrix.

Note that matrix H can be computed easily by filtering matrix Q; In formula, this corresponds to $H = F^{(b_K>0)} \cdot Q \cdot F^{(M_K=UP)}$. The vector describing the joint probability of the completion time and the system state at completion after n time units is composed of (x+1) blocks; one for each level of matrix A. Let us denote such vector with $\nu(n)$ and its entries with $\nu_i(n)$, $0 \leq i \leq x$.

By starting from an initial condition $\nu_0(0)$, the computation of the completion time can be carried on recursively as follows:

$$\nu_i(n) = \begin{cases} \nu_0(n-1)\bar{H} & i = 0 \\ \nu_i(n-1)\bar{H} + \nu_{i-1}(n-1)H & 1 \leq i \leq x-1 \\ \nu_{x-1}(n-1)H + \nu_x(n) & i = x \end{cases}$$

The probability that the completion time is smaller or equal to n is equal to the sum of the entries composing block $\nu_x(n)$.

As final remarks, we observe that the method allows the user to:

- compute the time to completion for any initial condition. This include steady state a.k.a. we impose the steady state distribution as initial condition $\nu_0(0)$;
- the method remains feasible for different system layout as long as it is possible to define the matrices $\bar{H}$ and H by isolating the states of the machine that generates the output of the system.

4. Numerical Results

In this section the proposed method is used to provide experimental evidences of how the time to completion of a lot is affected by the critical degradation level in which a machine is stopped to perform preventive maintenance. The first part of the section is used to present the problem. This is done by analyzing the optimal behavior of three systems according to different requirements.

In the second part of the section, we describe the use of the method in the context of a real industrial case.

4.1. Numerical illustrations

This section is used to show how preventive maintenance affects the lot completion time of a given lot size when degrading components are present in the system. In order to better appreciate the impact of the degrading component we decided to work in a flattened scenario i.e. we considered a building block composed of two single failure machines having geometric up and down times connected by a buffer having capacity $B = 10$. The two machines are identical and are characterized by a mean time to failure equal to 100 and mean time to repair equal to 10 time units. Accordingly, their transition diagram corresponds to the one depicted in Figure 3.

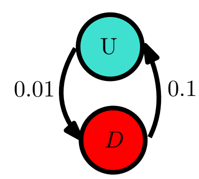

Figure 3: DTMC two single failure machine with geometric up and down times.

The decision to use these parameters as base-ground model is due to two main reasons: i) having a production line that is balanced and composed of machines characterized by an efficiency that is consistent with real-world parameters allows us to appreciate only the effect of the degrading component; ii) Having geometrically distributed failures and repairs reflects the scenario in which the only statistics available are the average of the failure and repair times. Therefore, no estimation of the distributions can be performed.

The building block is coupled with a degrading component characterized by a DTMC depicted in Figure 4 where: i) d corresponds to the degradation probability; ii) $p_{C,l}$ corresponds to the failure probability of the lth degradation level; $1/r_{CCM}$ and $1/r_{CPM}$ are the mean durations of corrective and preventive maintenance, respectively.

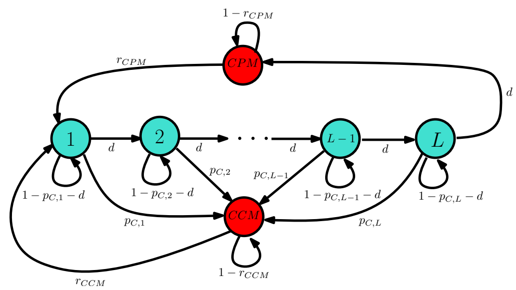

Figure 4: DTMC describing the degrading component.

Without losing generality, the degrading component is assumed to be part of the upstream machine[1], M_1. Thus, T_2 coincides with the state diagram depicted in Figure 3 whereas T_1 arises from the Kronecker product between the diagrams in Figures 3 and 4.

We considered three degrading components that differ from each other because of a single parameter. This allows us to show that a slight change in a parameter corresponds to significant changes in the time of completion of a lot. The failure probability of the degrading component is equal to $p_{C,l} = l \cdot 0.001$ and the average time for performing preventive maintenance is equal to $r_{CPM} = 0.5$ for all the systems. After preventive mainenance the degrading component is assumed to return in an as good as new state. Therefore, the effect between CM and PM relies only on the average length of the maintenance.

The degrading component of the first system has degradation probability equal to $d = 0.1$ and the average time required for corrective maintenance is $r_{CCM} = 0.1$. The second system has a degrading component with the same time to repair as the first, but with a degradation probability equal to $d = 0.2$. The degrading component of the third system has degradation probability equal to $d = 0.1$, but the average time required for corrective maintenance is $r_{CCM} = 0.05$. As a consequence, if L is fixed, system 1 has the highest efficiency whereas system 2 and 3 have the same efficiency due to the fact that system 2 reaches preventive maintenance twice faster than system 3 but its corrective maintenance requires half the time of system 3. Table 2 provides a summary of the parameters of the three systems.

Since the lot completion time is dependent on the service level, the lot size and makespan, we analyzed these three parameters in isolation by means of two different optimization problems. The first optimization problem focuses on the service level and the lot size whereas the third focus on the makespan.

The computation of a single evaluation requires less than a second whereas each optimization problem has been computed in 45 seconds by using a JAVA prototype on common hardware.

[1]Reversibility of the completion time has been experimentally shown in [68].

System	p_1, p_2	r_1, r_2	$p_{C,1}$	$p_{C,l} - p_{C,(l-1)}$	d	r_{CCM}	r_{CPM}
1	0.01	0.1	0.001	0.001	0.1	0.1	0.5
2	0.01	0.1	0.001	0.001	0.2	0.1	0.5
3	0.01	0.1	0.001	0.001	0.1	0.05	0.5

Table 2: The three different systems used for the experiments.

4.1.1. Minimal completion time as function of the service level

The first optimization problem aims to find the value of L that minimizes the time to completion of a lot for a given service level. Assume $C_l(x)$ to be the time to completion of a lot composed of x items of a system where preventive maintenance is performed when the component reaches the $(l+1)$ degradation level. We can formally define the optimization problem as:

$$L^* = \min_l \left[C_l(x) \right]. \tag{6}$$

subject to

$$SL(x, C(x)) \geq y \tag{7}$$

where y is the service level.

We considered a lot size $x = 250$ items and a maximum degradation level equal to 10. The service level is varied between 0.1 and 0.99. At the beginning of the analysis, the initial state of the system is as follows: both machines are operative, the degrading component is at its lowest degradation level and the buffer is empty.

The behavior of L^* for all the three cases is depicted in Figure 5. It can be noticed that the three curves differ from each other significantly but they share the same trend, i.e., as the required service level increases then L^* goes decreasing. This phenomenon can be explained by the fact that by performing preventive maintenance at large values of L, we increase the probability to find the upstream machine in corrective maintenance but we decrease the probability to put the upstream machine under preventive maintenance. Thus, there is a small probability that the lot is completed without observing down states. On the contrary, to meet high service levels, we have to admit the possibility that the upstream machine will end up in maintenance before completing the lot. In this scenario, small values of L guarantee shorter down times because preventive maintenance is more likely than corrective maintenance.

Furthermore, we can observe that all the curves differ because of their maximum and minimum. This is remarkable considering that the three systems share all the parameters but one. System 1 has the optimal L^* that changes the least whereas system 3 is the one whose optimal value changes the most. This was expected because system 1 has the degrading component with the smallest degradation probability and the smallest mean time to repair. Therefore, it is very unlikely that system 1 will reach large degradation levels before going in corrective maintenance and, even if it goes in preventive maintenance, the difference between time spent in preventive maintenance and the time spent in corrective maintenance is not large as for system 3.

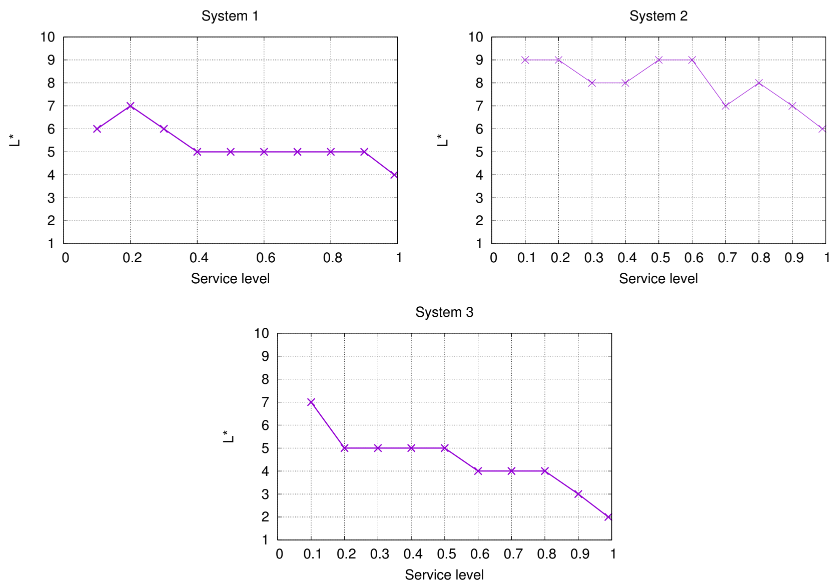

Figure 5: Optimal degradation level for the time to completion of a lot composed of 250 items as function of the service level.

Figure 6 depicts the time required to complete the lot under different preventive maintenance policies. The plots depict the curve corresponding to the optimal policies for the smallest and the largest service levels in Figure 5, the smallest degradation level possible ($L = 1$), the largest degradation level (L=10) and the curve generated by applying the optimal policy for each service level.

We can observe that system 3 is characterized by the largest differences between policies. This difference is an expected behavior because the degrading component of system 3 has the largest difference between r_{CCM} and r_{CPM}. Furthermore, it can be noticed that $L = 1$ always leads to a significant increment of the time to completion.

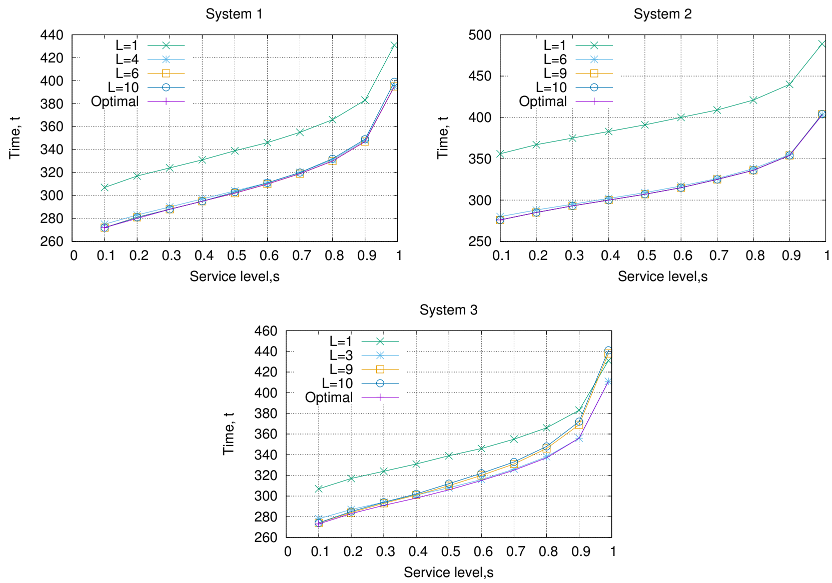

Figure 6: Time to completion of a lot composed of 250 items as function of the service level by applying different preventive maintenance policies.

4.1.2. Minimal completion time as function of the lot size

Here we apply the optimization problem described in equation (6) as function of the lot size instead of the service level.

We considered a service level equal to 99% and considered a maximum degradation level equal to $L = 10$. The lot size is varied between 1 and 250. The initial state of the system is: both machines are operative, the degrading component is at its lowest degradation level and the buffer is empty.

Results for all the three systems are depicted in Figure 7. We can notice that the optimal policies of system 1 and 2 have the same trend; namely, the maximal degradation level increases while the lot sizes increases. The optimal policy of system 3 instead remain stable to $L = 2$ for lot sizes greater than 10. This can be explained by the large mean time to repair of the degrading component of system 3. The gap between the corrective maintenance and preventive maintenance is such that it is more convenient to stop the machine immediately after the component degrades from $L = 2$ than to remain operative with a higher failure probability. For system 1 and 2, the difference between r_{CCM} and r_{CPM} is small enough to compensate an higher failure rate with a smaller number of preventive maintenances.

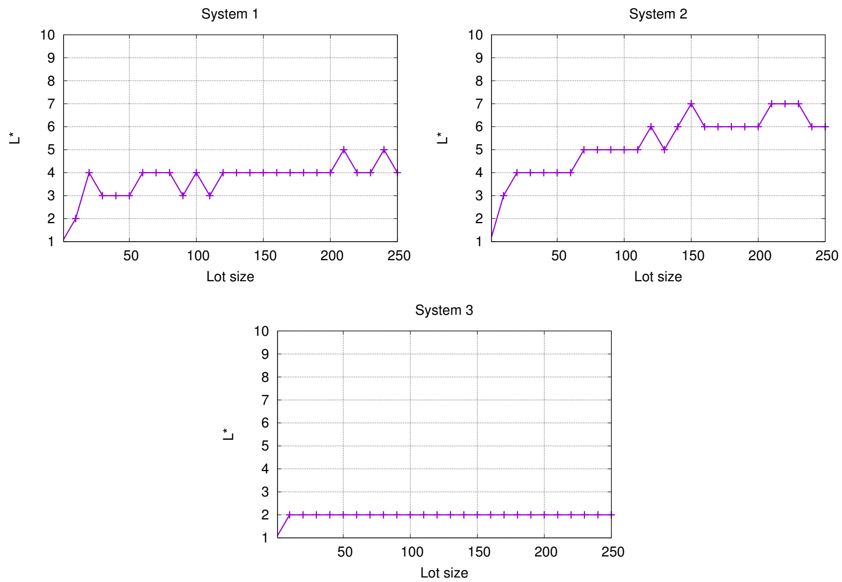

Figure 7: Optimal degradation level for the completion of a lot with 99% of confidence as function of the lot size.System 1 (top left), System 2 (top right) and System 3 (bottom).

Figure 8 reports the time required to complete the lot for different preventive maintenance policies. The plots depict the optimal policies for the smallest and the largest lot sizes in Figure 5, the smallest degradation level ($L = 1$), the largest degradation level (L=10) and the curve generated by applying the optimal policy for each service level (additional values of L are reported for the cases in which some of these values coincide).

We can observe that the impact of the policies becomes more marked for large lot sizes. This is expected because, for large lot sizes, the systems reach their steady state. Therefore, the completion of a larger part of the lot can be considered as the sum of i.d.d. random variables that depends only by the overall efficiency of the system. As a consequence, the largest is the lot and the more the optimal policy coincides with the degradation level that provides the best system efficiency.

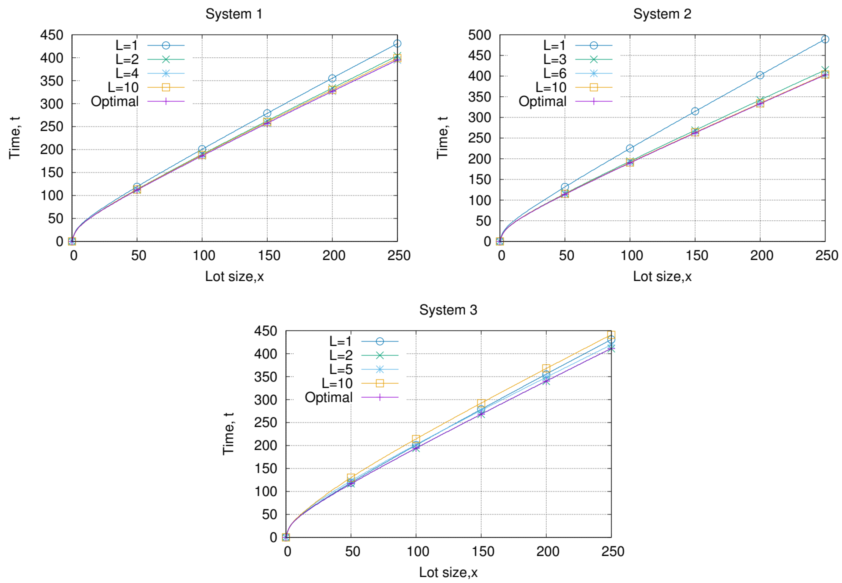

Figure 8: Time to completion of a lot with service level with 99% of confidence as function of the lot size by performing preventive maintenance at different degradation levels.

4.1.3. Maximum number of items as function of the makespan

The second optimization problem aims to find the degradation level L that maximizes the number of items completed with a service level of 99% for a given time interval (called makespan from now-on). Assume $Z_l(x)$ to be the number of items completed with 99% of confidence after n time units of a system where preventive maintenance is performed when the component reaches the $(l+1)$ degradation level. By using the definition of completion time in equation (4), we can formally define the optimization problem as:

$$L^* = \max_l \left[Z_l(n) \right] \tag{8}$$

subject to

$$Pr\{C_l(x) = n\} \geq y \tag{9}$$

where n is the desired makespan and y is the service level.

We considered a service level $y = 0.99$ and a maximum degradation level equal to $L = 10$. We varied the makespan between 1 and 400 time units. At the beginning of the analysis, machines are operative, the degrading component is at its lowest degradation level and the buffer is empty.

The behavior of L^* for all the three systems is depicted in Figure 9. We can notice that the optimal policy of system 1 changes significantly while increasing the makespan whereas the one of other two systems remain almost stable around $L = 2$. This phenomenon is explained by noticing that the optimization problem described in (8) depends only on the average downtime of the machines. System 1 has the degrading component with the highest efficiency; therefore, for large makespans there is still a possible trade off between trying to reduce the number of preventive maintenances by increasing the failure probability and accepting a large number of corrective maintenances to reduce the number of corrective maintenances.

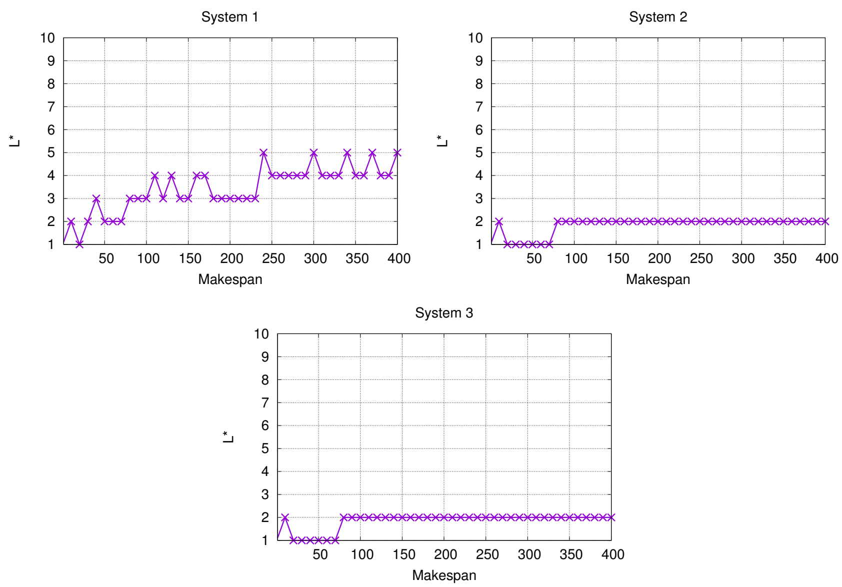

Figure 9: Optimal degradation level for the maximization of the number of items completed with a confidence of 99% as function of the makespan.

Figure 10 depicts the number of items completed for different preventive maintenance policies. The plots depict the optimal policies for the smallest and the largest makespans in Figure 5, the smallest degradation level ($L = 1$), the largest degradation level (L=10) and the curve generated by applying the optimal policy for each service level (additional values of L are reported for the cases in which some of these values coincide). We can observe that the systems that provide the largest differences between policies are system 2 and 3 which are the systems with the lowest efficiency.

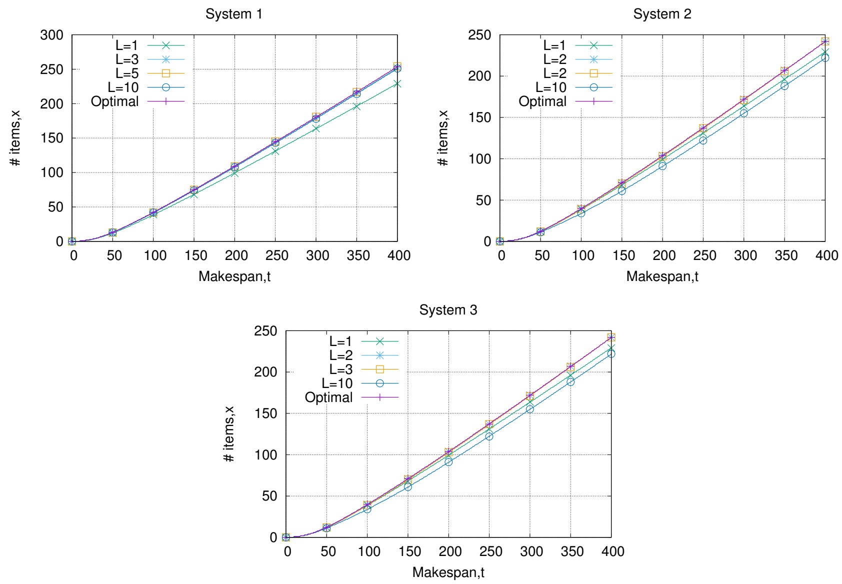

Figure 10: Number of completed items with 99% of confidence as function of the makespan by performing preventive maintenance at different degradation levels.

4.2. Application to a Real Industrial Case

The proposed method has been applied to a real Flexible Manufacturing System (FMS) used for machining titanium parts for the aeronautics industry, in the context of a tier 1 part supplier. This production scenario is characterized by a high pressure on the quality of the processed parts coupled with strict requirements on the respect of the fixed due-date performance. Due to the large amount of material removed in machining, machine deterioration is observed. Thus, the main challenge in this context is to develop effective condition based maintenance policies which do not interfere with the service level of the system.

4.2.1. Description of the system

The FMS considered in this study is composed of two highly automated flexible machining centers and additional material handling units. The high flexibility of the system allows the production system to be capable of running several part types concurrently. Before production, the parts are clamped on pallets. A schematic representation of the system is shown in Fig. **??**. A description of the main components follows:

- M_1 a 4-axis milling machine
- M_2 a 5-axis milling machine
- Pallet storage unit on 3 levels - PSU

- Three loading/unloading stations for parts - L/U S
- Shuttle for moving pallets inside the system - SH
- Cutting tools storage units - TSU

The main interactions of the FMS system units during operation can be described as follows:

1. Raw work-pieces enter into the system at one of the three load/unload station.
2. The transportation shuttle transports the loaded raw part-fixture assembly either to the roughing machine M_1 or to the pallet storage unit.
3. A raw part is transported by the shuttle to M_1 (4-axes) machine for rough machining operation. After the end of the rough machining operation the part is unloaded from M_1 by the transportation shuttle and then proceeds either to the finishing machine M_2 (5-axes) or to the pallet storage unit.
4. The transportation shuttle loads the finish machining, M_2 with a part that has just finished the roughing operation.
5. After a part completes finish machining operation at M_2, the shuttle unloads the finished part from the machine and stores it in the pallet storage unit. Finally all the finished parts are disengaged from the fixtures at the load/unload station and exit the system.

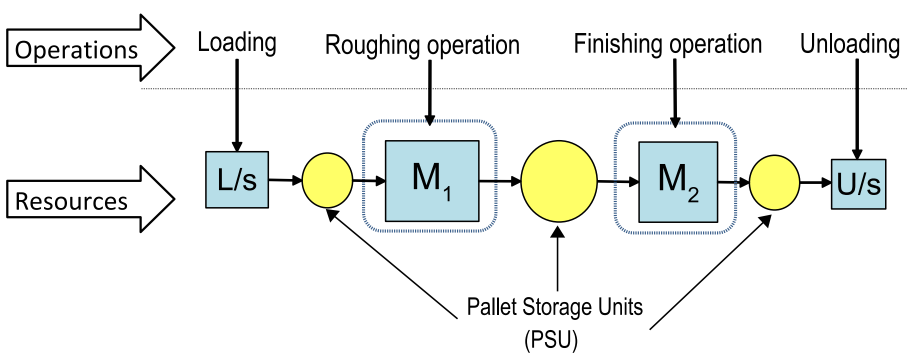

Figure 11: Schematic layout and material part flow in the FMS system

Currently, age based maintenance is carried out based on the information available in the maintenance manual, which is provided by the machine tool builder. Therefore maintenance is performed based on predetermined time intervals and this policy does not consider condition monitoring information about machine components. However, in the proposed approach a newly developed sensor network for condition monitoring is installed for the (4-axes) rough milling machine M_1, therefore the degradation modeling is considered only for this machine. The signals collected from the sensor networks are used as indicators for the degradation level of critical components in which the degradation modeling is based on.

4.2.2. FMS Modeling

A specific set of assumptions is used to model the behavior of the considered FMS.

- The transportation time required by the transportation shuttle is very short compared to the machining cycles of both the M_1 and M_2. Therefore, it can be neglected.
- Small amount of time is required for loading raw parts if compared to the machining cycle time. Hence, M_1 is never starved.
- The available storage spaces in the storage unit are sufficiently big to handle the finished parts that exit from M_2 and the unloading of a finished part requires negligible time. Therefore, M_2 is never blocked.
- The processing times of the two machines have been scaled to the time units. As a consequence, M_1 and M_2 are synchronized.

Under these realistic assumptions the system can be modeled as a two-machine line with a roughing machine (M_1) and a finishing machine (M_2), connected by a buffer of capacity $B = 20$.

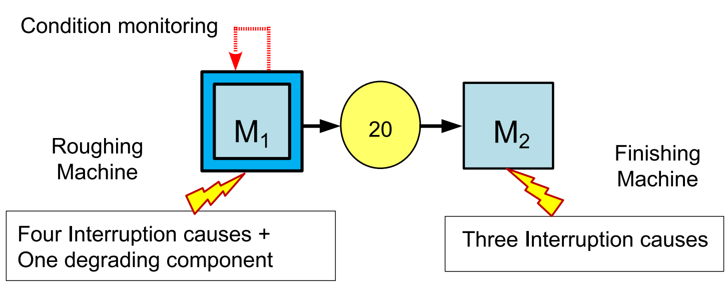

Figure 12: Flexible manufacturing system model.

4.2.3. Machine Degradation Models

In order to capture the behavior of the machines and to make an estimation of the model parameters, data about failure modes and their duration were collected from the production monitoring system. From such analysis, that does not take in consideration the effect of degrading components, three different classes of interruptions for each machine were classified. For each failure, the corresponding mean time to failure (MTTF) and mean time to repair (MTTR) were estimated. The values are reported in Table 3. The behavior of the two

i	$p_{i,1}$	$p_{i,2}$	$p_{i,3}$	$r_{i,1}$	$r_{i,2}$	$r_{i,3}$
1	0.002976	0.000937	0.000142	0.370370	0.709219	0.15432
2	0.002232	0.000267	0.000083	0.460829	0.571428	0.132100

Table 3: Estimated failures and repair probability of the roughing and the finishing machine

machines in isolation from degrading components is described by the DTMC depicted in Figure 13

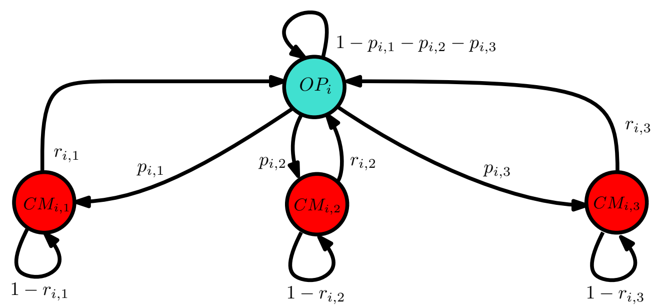

Figure 13: DTMC describing the machine behavior isolated from degrading components.

where OP_i corresponds to the state in which M_i is operative and state $CM_{i,j}$ represents the jth failure of M_i. Accordingly, $p_{i,j}$ is the probability with which M_i fails because of the occurrence of the jth failure and $r_{i,j}$ is the probability with which M_i will return operative from failure j in the next time unit. In reference to Figure 13, the DTMC probability matrix, denoted with A, is defined as follows

$$\begin{vmatrix} 1 - p_{i,1} - p_{i,2} - p_{i,3} & p_{i,1} & p_{i,2} & p_{i,3} \\ r_{i,1} & 1 - r_{i,1} & 0 & 0 \\ r_{i,2} & 0 & 1 - r_{i,2} & 0 \\ r_{i,3} & 0 & 0 & 1 - r_{i,3} \end{vmatrix}$$

and its corresponding reward vector is $\mu_A = |1, 0, 0, 0|$.

For what concern the finishing machine, degrading components having a significant impact on the overall machine behaviour were not identified, as the material removal rate is lower than the roughing machine. As a consequence, the transition probability matrix of the M_2 is $T_2 = A$ and its reward vector is equal to $\mu_2 = \mu_A$. On the contrary, with respect to the roughing machine, a sensor network allowed us to monitor a degrading critical component in such a way that we were able to distinguish different degradation levels. The state-transition diagram of the DTMC describing the degradation of the critical component for the roughing machine corresponds to the one depicted in Figure 4 where:

- $p_{C,l}$ is the probability to incur in a failure at the lth degradation level with $p_{C,1} = 0.001$ and $p_{C,i} = p_{C,l-1} + 0.001$, $2 \leq l \leq L$;

- $r_{CCM} = 0.1$ and $r_{CPM} = 0.5$ corresponds to the MTTR of corrective and preventive maintenances, respectively;
- $d = 0.1$ represents the probability to go through degradation states.

In sake of synthesis, we do not report the full transition matrix describing the behavior depicted in Figure 4. The DTMC describing the overall behavior of the roughing machine is generated by the synchronization of the DTMC describing the failures of M_1 and the failures of its degrading component. More formally:

$$T_1 = A \otimes C$$

Similarly, the reward vector associated to M_1 is equal to $\mu_1 = \mu_A \otimes \mu_C$. The partitioning of T_1 and T_2 described in equation (1) is straightforward by considering the associated reward vectors.

4.2.4. System Behavior

The proposed method is used to evaluate the lot completion time distribution and drive specific decisions on the preventive maintenance policy of the system described in 4.2. Such analysis has practical significance considering the frequency of carrying out maintenance and production planning and their direct impact on respecting customer order due dates. Thus, the numerical experiments conducted in this section show how the proposed approach supports the joint maintenance and production plan analysis and demonstrate its vital contribution in decision making.

In practice, such a joint analysis can explore all the possible combinations of maintenance policies and production plans, but for the sake of brevity here we limit the demonstration on two production lots sizes and three maintenance policies. Two different production lot sizes of 50 units and 200 units are selected. In addition, the three maintenance policies are defined based on the degradation level of the critical component from which the maintenance action is triggered. With reference to the specific component modeled in Figure 4 these degradation states are indicated by index L and they are the basis for defining the maintenance policies indicated by π_L below.

- (π_2): Preventive maintenance at degradation state $L = 2$ i.e., early degradation.
- (π_5): Preventive maintenance at degradation state $L = 5$ i.e., average degradation.
- (π_{10}): Preventive maintenance at degradation state $L = 10$ i.e., higher degradation.

The three maintenance policies are analyzed under the two production scenarios which are defined based on the lot sizes. The results obtained under the two scenarios are presented as follows.

Scenario 1: The service level of the system as a function of the target lot completion time is reported in Figure 14 (a). Considering a lot size of 50 parts and a target lot completion time of 55 time unit, the maintenance policy preference order is $\pi_5 \to \pi_{10} \to \pi_2$, providing a service level of 0.58, 0.80 and 0.84, respectively. However if we change the target lot completion time of the same lot size to 52 time units (indicated in broken lines) the preference order of the maintenance policies changes to $\pi_{10} \to \pi_5 \to \pi_2$ with a service level of 0.20, 0.60 and 0.68.

Scenario 2: In this scenario the service level is evaluated for a production lot size of 200 parts. The same analysis of Scenario 1 is performed. Results are reported in Figure 14 (b). In this case we focus our attention on comparing two of the best performing maintenance strategies for improved lot completion time, i.e., π_{10} and π_5. As it can be noticed, the choice of the best maintenance policy is dependent on the target lot completion time. The maintenance policy that offers a higher service level for a lot size of 200 parts and a completion time of less than 211 is the (π_{10}) policy. Considering a completion time of 211 both (π_{10}) and (π_5) give the same service level. However, for a completion time greater than 211 the maintenance policy with high service level changes from (π_{10}) to (π_5). The switchover of the two maintenance policies and the point where the switching takes place is schematically shown in Figure 14 (b).

This analysis highlights the importance of considering the impact of preventive maintenance policies on the service level of the system, as the same maintenance policy can prove to be sub-performing for different target lot completion times. In other words, if the preventive maintenance policy is kept fixed while changing the production plan, then the service level of the system may drastically decrease. It is worth to remind that different degradation dynamics can lead to different optimal policies. This motivates the need for system engineering tools supporting these decisions.

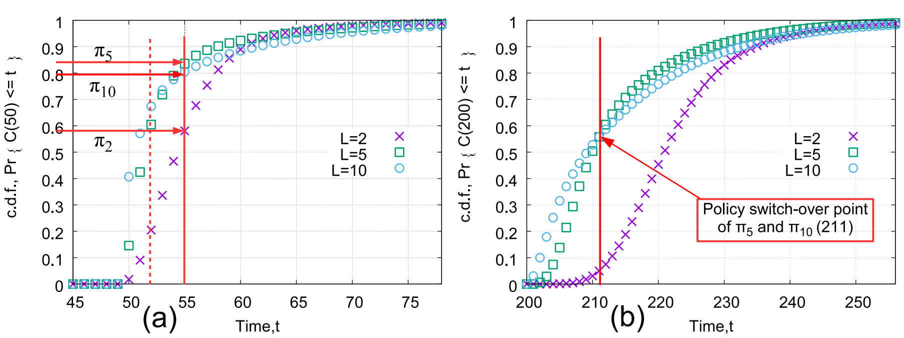

Figure 14: Service level as a function of time for lots of 50 parts (a) 200 parts (b)

5. Conclusions

The paper has shown that the preventive maintenance policy significantly affects the time to completion of a lot. We focused on production lines composed of two synchronous machines decoupled by a buffer. First, we considered three baseline systems and analyzed them in detail; the analysis has put on the spotlight the sensitivity of optimal maintenance policies to small variations of the parameters. Secondly, we illustrated a real industrial case characterized by multi-stage processing of parts in the aeronautics industry. This use case has shown the impact of different maintenance policies and their relevance in decision making where machines' components are subject to degradation and target service levels has to be guaranteed robustly.

The method used for obtaining the results have been illustrated in such a way that it is feasible for production lines of arbitrary length and extremely general synchronous machines. As defined, the method has a broad sphere of application for different system layouts, only requiring minor modifications.

Due to its flexibility, the proposed method enables a fast evaluation of solutions that are needed for day to day and shift to shift decisions considering dynamic changes at the shop floor level. This makes the method suitable for being part of decision support tools where information is continually gathered about critical equipment health and dynamic customer orders and production deadlines need to be met.

The paper opens many possible research developments. The first is to exploit the generality of the method by coupling it with the inference of PH distributions for the modeling of failures and repairs of the components. Secondly, we aim to introduce complex multi-dimensional degradations in order to investigate the application of multi-dimensional preventive maintenance policies.

Extension of this work will consider further challenges such as, multiple and heterogeneous lots, correlated degradations of multiple critical components, the analysis of state-based opportunistic maintenance policies and production plans with different product mixes and deadlines. Furthermore, this research plans to investigate completely different approaches in the future, such as continuous degradations instead of discrete.

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