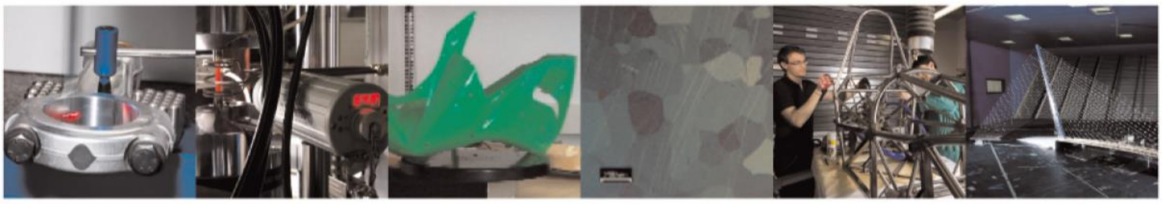

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Impact of opportunistic maintenance on manufacturing system performance

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Opportunistic maintenance is an effective strategy to reduce the interference between maintenance and production operations in multi-stage manufacturing systems. However, its application in industry is still limited due to the difficulty to predict its impact on system performance. This paper develops a methodology for estimating the production gains that can be generated by exploiting opportunistic windows to perform preventive maintenance tasks during production. The characteristic behaviour of the system is investigated and suitable policies for implementing opportunistic maintenance actions are derived. The industrial benefits are demonstrated with reference to a real industrial case in the high-volume production of ready-to-assemble furniture.

Maintenance; Production System; Opportunity window.

1. Introduction, motivation and objectives

Maintenance activities are traditionally considered in conflict with production operations [1]. Indeed, although preventive maintenance preserves the equipment against degradation, thus reducing the need for complex and expensive corrective actions, it negatively affects the equipment availability. This, in turn, undermines the achievement of production targets, especially in the context of high-volume manufacturing systems, such as those found in automotive component manufacturing, in the pharmaceutical, and in the food industry.

In order to reduce this undesired effect, considerable effort has been devoted towards the development of policies for a better synchronization between preventive maintenance and production operations [2]. Among preventive maintenance control policies, opportunistic maintenance is an effective strategy to reduce the impact of maintenance operations in multi-stage manufacturing systems [3]. According to this strategy, preventive maintenance tasks should be performed when suitable opportunity windows become available due to the dynamic behavior of the system. Opportunity windows are defined as specific time intervals, generated by favorable system conditions, in which preventive maintenance actions can be implemented with minor effect on the production performance of the system. By exploiting these opportunity windows, better synchronization between production and maintenance operations can be achieved, thus reducing the maintenance impact on system performance [4].

The concept of Opportunistic Maintenance was introduced in [5], but applications in industry have been very limited, mainly due to the difficulty in calculating the duration of opportunistic windows, in predicting the effect of specific maintenance actions on the system performance and due to the lack of technologies supporting the on-line observation of the system states. However, the recent developments of industry 4.0 technologies and the improvements in production monitoring systems have provided new capabilities for achieving effective implementation of this strategy in industry and have revitalized research in this field. In [6] a strategy to identify and predict the so-called ‘opportunistic zones’ in a system was developed. In [7] Passive and Active Maintenance Opportunity Windows (PMOW and AMOW) were defined. Passive windows exploit the idle time caused by the downtime of other machines in the system [8]. Methods to calculate the duration of passive windows based on the analysis of starvation and blocking propagation times throughout the production line were proposed in [9] and [10]. Conversely, active windows exploit the inventory stored in the buffers to absorb a minor intervention on the machine, without interrupting the material flow in the system ([11], [12]). Although the mentioned papers contributed to the formalization of the problem, the definition of optimal opportunistic maintenance policies and the estimate of their impact on system throughput remains a challenging issue for practitioners, limiting the applications of opportunistic maintenance in real systems.

This paper proposes for the first time a modeling framework and a methodology to predict the effect of frequency and duration of opportunistic maintenance actions on system performance. This in turn allows the derivation of optimal opportunistic maintenance policies. The application of the approach to a real industrial case in the furniture industry shows that significant benefits can be achieved by smartly exploiting existing opportunities for maintenance, in safe and controlled conditions.

2. System description

The considered system is formed by K machines and K-1 buffers of finite capacity, configured in serial layout (Figure 1). Machines are denoted as M_k, $k=1,..,K$ and buffers are denoted as B_k with $k=1,..,K-1$. Finite capacity buffers (yellow circles) can either model physical conveyors or the implementation of kanban production control rules, regulating the material flow release at each stage [13]. The capacity of each buffer is N_k.

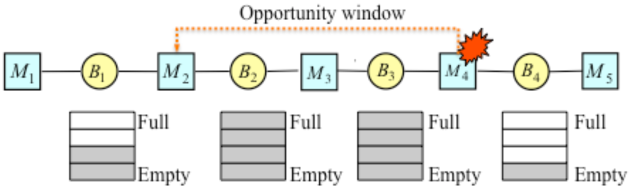


Figure 1. Representation of the analyzed manufacturing system and example of passive maintenance opportunity window.

2.1. Single stage model

The dynamics of each stage is modeled by a general continuous-time, discrete-state Markov chain. This setup allows to analyze a wide set of different machine behavior within a unique framework. For example, unreliable machines characterized by generally distributed up and down times and deterministic processing rates can be considered, thus making the approach applicable to a wide set of real automated manufacturing systems. Each machine M_k is modeled with I_k states belonging to the set S_k. The dynamics of each machine in visiting its states is captured by the transition rate matrix λ_k, that is a square matrix of size I_k. Moreover, the processing rates of the various states are defined in the vector μ_k having I_k entries; in the generic state i, M_k produces at a rate of $\mu_k[i]$ parts per minute. Therefore, a state i with $\mu_k[i]>0$ can be considered as an operational state for stage M_k, while a state i with $\mu_k[i]= 0$ represents a failure state of machine M_k.

2.2. Material flow dynamics

The discrete asynchronous flow of parts in the system is modeled as a continuous material flow. Machines act has valves processing the material flow at different rates in each specific state. Stage M_k is blocked by machine M_j, with $j>k$, if M_j is in a state i such that $\mu_{j,}[i]= 0$ and all the buffers between the two stations, B_k, B_{k+1}, ..,$B_{j-1,}$ are full. Stage M_K is starved by stage M_j, with $j<k$, if M_j is in a state i such that $\mu_{j,}[i]= 0$ and all the buffers between the two stations, B_j, B_{j+1}, ..,$B_{k-1,}$ are empty. Stage M_K is never blocked, i.e., an infinite amount of space is available to store finished products. Stage M_1 is never starved, i.e., an unlimited supply of raw parts is assumed. Operational Dependent Transitions are considered, i.e., a machine cannot make transitions to other states if it is starved or blocked.

2.3. Opportunistic maintenance

Although the developed method is amenable of extension to include active maintenance opportunity windows, in this paper only passive maintenance opportunity windows are considered. Whenever machine M_k is blocked due to down state i of machine M_j with $j>i$, an opportunity window is observed. For example, in Figure 1 an opportunity window at machine M_2 is generated by a failure at machine M_4. Each opportunity window can be exploited by activating an opportunistic maintenance action. While $f_{k,}[j,i]$ denotes the fraction of times the opportunistic maintenance action is activated on M_k, once a PMOW generated by down state i at M_j is observed, $T_k[j,i]$ is defined as the average duration of the opportunistic maintenance action activated on M_k, in the PMOW generated by down state i at M_j. The implementation of an opportunistic maintenance action forces the machine to a non-operational state, characterized by processing rate equal to zero. If the preventive maintenance task duration at M_k is lower than the time to recover the failure of M_j and to propagate the unblocking of M_k, than the maintenance action does not affect the throughput.

2.4. Performance measures

The main performance measures of interest are as follows:

- Average production rate of the system, denoted by E.
- Average inventory in the buffer B_k, denoted by b_k.
- Total average inventory of the system, i.e. the *WIP* (Work In Progress).

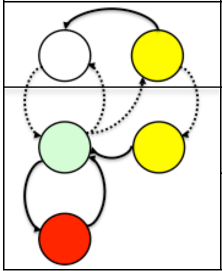
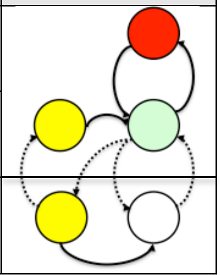
3. Description of the method

3.1 Analysis of a two-machine line

With the objective to derive estimates of the target performance measures of the system, an analytical approach is proposed. In this section, the method is presented in detail for a simple two-machine system and extended to longer lines in the next section. The approach relies on the method originally proposed in [14]. In that case, two-machine lines where machines can have different behaviour depending on the specific region in the buffer level space, delimited by thresholds, was proposed. Since passive maintenance opportunity windows can trigger maintenance actions only at the system boundaries, i.e. when the first machine is blocked or the second machine is starved, then the problem analysed in this paper falls under the same settings.

Considering the case of machines having a single operational and down state, the behaviour of the two machines in different regions of the buffer is shown in Table 1, where the green state is the operational state, the red state is the failure state, the yellow state is the maintenance state and the white state is the idle state. Focusing on M_1, in the interior and lower buffer levels, the machine can be operational or failed. Once M_2 has failed, the buffer level starts to grow and will eventually hit the upper threshold. Without opportunistic maintenance, M_1 would get blocked. However, the possibility of exploiting this opportunity window for maintenance generates a control that affects the system behaviour. In this case, two scenarios are triggered. If the action is implemented at M_1, with frequency $f_1[2,1]$, then the machine goes in the maintenance state at full buffer level. If the action is not implemented, then M_1 gets blocked. Once in maintenance state, two scenarios are enabled: if the maintenance action is faster than the time to unblock M_1, then M_1 goes to the blocking state with rate $1/T_1[2,1]$. Otherwise, M_1 remains in the maintenance state and the buffer starts decreasing, since M_2 has been repaired. Once back in the interior levels, the machine can recover from maintenance with rate $1/T_1[2,1]$ and goes back to the operational state. The dynamics is similar also for M_2. Once described the dynamics of the behaviour of the machines in the system as a function of the buffer level region, the method proposed in [14] can be used to compute the system throughput, E, and the average buffer level, b, of the two-machine system.

Table 1 Machine state-transition diagram as a function of the buffer level.

Behavior M_1	Buffer level	Behavior M2
	Full	
	Interior	
	Empty	

3.2 Analysis of longer lines

The analysis has been extended to longer lines by adopting the decomposition approach that was recently proposed in [15]. The idea of the decomposition approach is to decompose the K-machine system into a set of K-1 two-machine one-buffer sub-systems $l(k)$, i.e. one for each buffer in the original system. The performance of each sub-system where machines are subject to opportunistic maintenance can be evaluated with the exact analytical method proposed in the previous section. The decomposition equations for such system settings are provided in [15]. The system performance measures can be estimated as:

$$E = E(k) \quad WIP = \sum_{k=1}^{K-1} b(k) \tag{1}$$

This method was proved to be accurate in estimating the system performance, showing errors against simulation below 2% on a wide set of 100 test systems with randomly generated data.

4. Numerical results and system behavior

A set of experiments has been conducted with the objective to investigate the impact of opportunistic maintenance parameters and control variables on the overall system performance. A three-machine line has been considered as the reference case. The second machine of the line is the bottleneck with respect to the production rate. System parameters are reported in table 2.

Table 2. Parameters of the systems analysed in the experiments.

System Data
$\lambda_k = \begin{vmatrix} -p_k & p_k \\ r_k & -r_k \end{vmatrix}, \mu_k = [1,0]$
with $p_1=0.022$, $r_1=0.12$, $\alpha_1=4.1$, $p_2=0.025$, $r_2=0.14$, $\alpha_2=4.09$, $p_3=0.016$, $r_3=0.09$, $\alpha_3=4.15$; $N_1= N_2 =5$. The parameter α is expressed in parts per minute.

4.1 Impact of opportunistic maintenance on system throughput

The first analysis is focused on the impact of an opportunistic maintenance action, activated on machine M_1 by exploiting the opportunity window generated by machine M_2, on the system throughput. Results are shown in Figure 1. The mean duration of the opportunistic maintenance action, $T_1[2,1]$, has been varied between 4 and 15 minutes and different values of the maintenance activation frequency, $f_1[2,1]$, are considered.

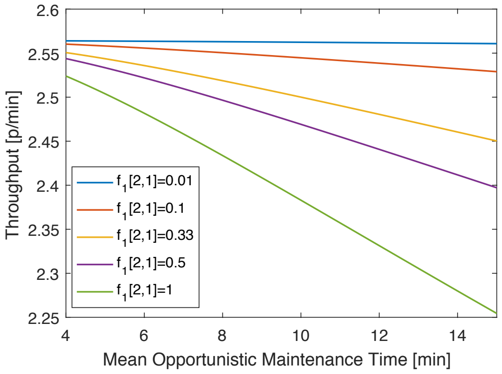


Figure 2. Impact of opportunistic maintenance at M_1 on the throughput.

By observing the system behaviour represented in Figure 2, the following considerations hold:

- Even short and rare maintenance actions (e.g. see the red line) have an impact on the system throughput, because they directly affect the system dynamics.
- The frequency f represents how often the opportunistic maintenance is activated when the opportunity window is unlocked by the system state. Very frequent and long maintenance actions can lead to considerable throughput losses. The throughput loss for a maintenance action of 12 minutes and 100% activation frequency (green line) is 10%.
- However, if the parameters of opportunistic maintenance are properly set, very long maintenance opportunities can be unlocked, with minor impact on the throughput. For example, by observing the yellow line, an opportunistic maintenance action of 15 minutes can be implemented by only loosing the 4% of the throughput. Over a finite time horizon, for example in a 8 hours shift, this means gaining about 34 minutes of maintenance time on M_1, at the cost of loosing only the production of 50 parts. By performing the same maintenance actions after the shift, as typically done in current industrial settings, this would cause a production loss of about 90 parts.

These considerations lead to the need of investigating the gain of optimized opportunistic maintenance policies with respect to other common maintenance policies designed without taking into consideration the synchronization between production and maintenance tasks. This analysis is performed in the next section.

4.2 Comparison among preventive maintenance policies

In this paragraph, the behaviour of the following preventive maintenance policies is compared:

- *Preventive Maintenance, during shift changes* (Policy 1): maintenance actions are performed every fixed time interval, typically at the end of the shift, and the whole line is stopped. This policy corresponds to a totally decoupled production and maintenance strategy.
- *Preventive Maintenance*, *at random times during production* (Policy 2): Maintenance is carried out randomly during production, without considering the system condition. This policy entails a partially coupled production and maintenance strategy.
- *Opportunistic Maintenance* (Policy 3): the maintenance actions are performed during maintenance opportunity windows. This policy entails a totally synchronized production and maintenance strategy.

The comparison is performed as follows. A preventive maintenance action, characterized by a given time duration, is allocated at the end of each shift, according to policy 1, and the cumulated daily production is computed. Then, the same maintenance action is activated during production, keeping the same number of parts produced between subsequent maintenance actions, but neglecting the specific state of the system, according to policy 2. Finally, the same maintenance action is activated during production, keeping the same number of parts produced between subsequent maintenance actions, in opportunistic time windows, according to policy 3. Each policy is then compared in terms of cumulated daily production, considering three shifts per day. Results are reported in Figure 3, where the mean duration of the maintenance activity is varied between 5 and 11 minutes. The following considerations hold:

- Policy 1 always underperforms with respect to the other policies, since the maintenance is performed in non-operational times. In the worst-case scenario, around 100 parts that could have been produced daily, with a better synchronization of maintenance and production, are lost.
- The opportunistic maintenance policy (policy 3) always outperforms the preventive maintenance policy activated randomly during production. Indeed, by randomly applying preventive maintenance during production a significant impact on the throughput can be observed. For example, for maintenance actions of 10 minutes, 60 additional parts can be produced with opportunistic maintenance.

These results show that the benefits of implementing opportunistic maintenance are particularly evident in high-throughput manufacturing systems, where significant pressure on maintaining the system operational is found. It is worth to highlight that usually in real settings, maintenance actions implemented outside the shift time are more expensive [9], and this further supports the use of opportunistic policies.

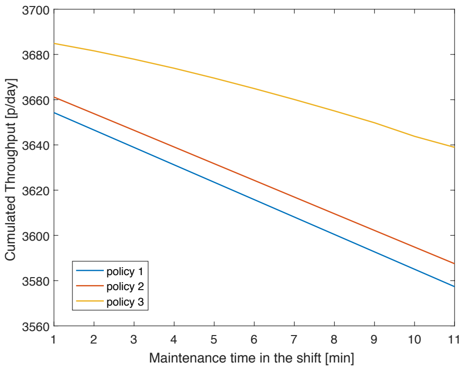


Figure 3. Daily cumulated throughput for each maintenance policy.

5. Real case study

The proposed method has been validated through the application to a real industrial case in the furniture sector. The analysed system produces ready-to-assemble, multi-variant drawers for kitchens. Due to the high competitiveness of the sector and the relative low value of the product, the profitability of the company grounds on high production rates and very low scrap rates.

The specific focus of the use case is on a completely automated multi-stage line producing drawer slides (see Figure 4). Each slide is composed by upper, lower, middle parts and the damper travelling together on a conveyor belt along the line. The current process includes different machines such as rotary tables providing components, pick and place robots, stamping and greasing stations. The line has been modelled as a five-stage system. Station 1 welds the brackets on the part. This is the most complex operation, and this station is the slowest station in the line. Station 2 is composed by two electro-magnetic distributors that insert a hook in the slide, after having greased it. Station 3 and Station 4 clean the part, and assembles together the upper and lower part to the middle part and the damper. The last station of the line, i.e. station 5, performs final stamping, inspections and unloads the finished product. The operational and failure times were obtained by analyzing the timed state sequence of the various stations, recorded and stored in the company database. The performance of the system in the current configuration and without opportunistic maintenance was evaluated and the results were validated through comparison with historical production data.

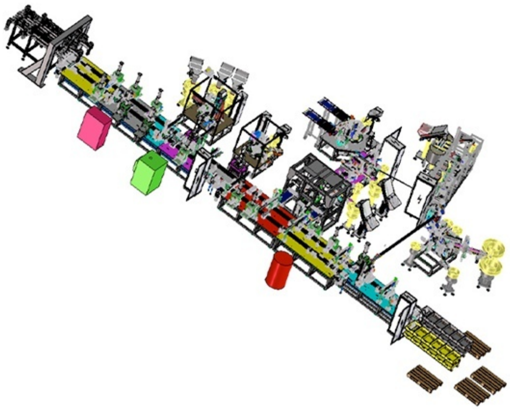


Figure 4. Real case production line.

According to the currently implemented policy, periodically minor preventive maintenance activities, suggested by the system integrator, are implemented. These activities are carried out at fixed time intervals, without taking into account the system state (policy 2). The goal of the study was to quantify the effect of a new opportunistic maintenance policy, to better synchronize these minor preventive maintenance actions with production operations (policy 3).

From the analysis of company data, a list of minor actions that have to be performed in order to prevent the equipment from major damages has been collected. In particular, station 2 has to be cleaned often in order to take out dust or other impurities from the sensors, due to the greasing operation. Moreover, the vibrating system providing the hook to the same station requires the operator's intervention consisting in periodically shuffling the parts to prevent components from remaining caught within the feeder. Typical durations (12 minutes) and frequencies (every 3 hours) of these maintenance activities have been estimated with the support of maintenance personnel and the performance of the system under policy 3 was estimated. Results are reported in Table 3. System data are omitted due to confidentiality reasons. As it can be noticed, by implementing the opportunistic maintenance policy, an increase in the daily production rate of about 5% can be achieved, corresponding to 480 parts/day. In one year, this would translate into a cumulative production gain of 120.000 parts, at the only cost of shifting to a more effective preventive and opportunistic maintenance policy.

Table 3. Real case study: comparison of maintenance policies.

Policy	**Production rate [Parts/Day]**	**Performance Improvement**
2	10800	0 (baseline case)
3	11280	+ 4.6%

6. Conclusions

This paper proposes a modeling framework and a methodology to predict the impact of opportunistic maintenance actions on the production logistics performance of manufacturing systems. The numerical results show that by properly setting the parameters of opportunistic maintenance actions, an effective synchronization of preventive maintenance and production operations can be achieved, thus simultaneously preserving the machine conditions while meeting production targets. The real case analysis highlights that high benefits can be achieved by implementing the developed methodology, even in demanding industrial contexts.

The theoretical work developed in this paper opens the way for further extensions to more complex problem settings. For example, the case where limited number of maintenance operators need to dynamically select among various possible preventive maintenance actions will be addressed. This extension will benefit from the design of a new information technology infrastructure to smoothly interact with the operators and support the adoption of opportunistic maintenance at large scale.

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