Assessing the Stochastic Dependence Effect on the Integrated Preventive Maintenance Scheduling and Production Planning

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Abstract

Integrating production planning and preventive maintenance (PM) scheduling is one of the most studied problems related to operations management. In fact, both decisions are highly interrelated. An efficient integration leads to cost optimization and high delivery reliability. In this paper, we evaluate the impact of the stochastic dependence on the integrated preventive maintenance scheduling and production planning. For this purpose, Cox Proportional Hazards Model (CPHM), based on the exponential survival distribution and an integer programming model are used. The results show that increasing the degree of dependence affects both production and maintenance costs and the system's available production capacity.

Keywords
Production planning, Preventive Maintenance, Multi-components systems, Stochastic Dependence, Integer Programming.

1. Introduction

Nowadays, companies are drastically competing due to hard constraints on the price-cost margin of goods and services. As a result, attaining high production performance becomes problematic and creates many challenges, notably in terms of production scheduling and preventive maintenance (PM) planning. Indeed, the relationship between these two activities has been characterized as mutually in conflict, especially when the production and maintenance planning are carried out independently. Such conflicts may result in an unsatisfied demand in production, due to equipment unavailability due to the non-respect of the time needed for maintenance activities (Berrichi et al. 2009). According to (Aghezzaf et al. 2008) and (Chung et al. 2009), communication and collaboration between maintenance and production are the main keys for successful planning in production systems. From this perspective, developing integrated planning and scheduling solutions lead to a considerable gain in productivity notably for multi-component systems. In addition, realistic production planning and PM planning need to consider the different dependencies between the system's components such as the stochastic dependence. It is important to mention that stochastic dependence occurs when the state of a component or its degradation can influence the states or degradation levels of other components (Keizer et al. 2017). Consequently, this influence makes the system availability increasingly degraded (Bahou et al. 2021). In this paper, we assess the stochastic dependence impact on the optimal production plans with preventive replacement. For this purpose, we extended the work presented by Bahou et al. (2021). The main contribution of this paper is the highlighting of the stochastic dependence effect on the integration of the production planning and the maintenance schedule. The paper is structured as follows. In Section 2, we present a literature review related to the subject. Then, we describe the problem in Section 3. Subsequently, a preliminary analysis will follow in Section 4. Finally, a conclusion and perspectives are provided in Section 5.

2. Literature Review

According to Budai et al. (2008), the integrated production planning and PM scheduling models are subdivided into four categories: High-level models considering process design problems, Optimal production quantity models, Production system models with buffer stocks in purpose to cope with breakdowns and optimizing production rates and preventive maintenance frequencies models to minimize the total cost including inventory, production, and maintenance costs. Ouali et al. (2002) developed an integrated maintenance and control strategy for optimizing the stock of the finished products produced by a production system, which is composed of one machine and producing one type of product. Thus, it considers the production plan as well as the availability of the necessary resources to carry out maintenance actions. Yao et al. (2005) integrated preventive maintenance and production policy. They proposed a model assuming non-negligible repair times. Frequently, machine failures can cause product quality deterioration or degradation. From this perspective, Salih Duffuaa et al. (2020) developed a model integrating production planning, preventive and corrective maintenance scheduling, and quality decisions for a single machine. More recently, Gómez et al. (2020) developed the same model for a continuous production system, with a single machine, subject to product quality deterioration. They proposed a dynamic sampling strategy to deal with the damages caused. Kenne and Nkeungoue (2008) proposed an integrated problem of corrective and preventive maintenance scheduling and production planning for a production system composed of several identical machines capable of producing different products, and subject to random failures. They developed a stochastic optimization model with two state variables, which are the machine age and the stock. Rezg et al. (2004) studied a production control policy based on the study of system availability. It is a model for the preventive maintenance optimization and control stock of a serial production line based on several machines. It also depends on the demand occurring at constant periodicities and quantities.

Cho and Parlar (1991) define multi-component system maintenance models as maintenance models concerned with studying optimal maintenance strategies for a system composed of several units of a machine or several pieces of equipment, which may or may not be dependent on each other. In this work, we are interested in multi-component systems that are stochastically dependent. Several works have focused on this aspect. For instance, Barros et al. (2003) proposed a preventive maintenance policy for a parallel two-component system, where the failure rate of one component in operation is increased by the failure effect of the other component. That leads to a stochastic dependence. Furthermore, Lai and Chen (2006) proposed a periodic replacement model for a two-unit system subject to stochastic interactions in failure rates. The adopted policy is an age-type replacement policy, which consists of replacing the two units at a certain age or in a failure event. The authors determine the optimal replacement age of the two units by minimizing the average total maintenance cost per unit of time. Satow and Osaki (2003) treated a two-component system where the failure rate of the first component follows the Poisson point process and considered it to cause damage on the second. Van Horenbeek and Pintelon (2013) studied the same case and three different scenarios. Each one occurs with a given probability. The first scenario consists of no damage being caused and replacing only the failed component. The second scenario occurs when the component failure causes the replacement of another component equally. Finally, the third scenario happens when the failure of the component causes the replacement of the entire system. Although, the authors have not provided any information about a stochastic dependence influence on the adopted policy. Zhang et al. (2013) considered that the components share the load in its simple form. They formulated the problem as a Markov decision process (MDP) to minimize maintenance costs. Finally, they showed that the dependence must be considered while taking a maintenance policy decision. They mention that the costs of neglecting this dependence significantly increases with the number of components and the degree of dependence. OldeKeizer et al. (2016) studied a parallel system whose components are assumed economically and stochastically dependent "load sharing type" and they showed that the deterioration rates depend on the number of operating components. Rasmekomen and Parlikad (2016) and Do et al. (2015) studied a multi-component system with failure rates depending on the states of the others. The authors, in the first work, showed that the interactions between the components can impact maintenance policies, such as CBM, using simulated annealing. The authors, in the second work, proposed rules for adaptive preventive maintenance and opportunistic maintenance in order to select one or several components to be maintained in regular time intervals. The "common-mode deterioration" occurs when several components may fail or deteriorate simultaneously. That means that the deterioration acceleration of one component is associated to the other components deterioration rates. Qianmei Feng et al. (2015) investigated this stochastic dependence. They were interested in the reliability of multi-component stent systems such small tubular mesh devices, which are inserted into a patient's narrowed arteries. Mercier and Pham (2014) proposed a two-component bivariate stochastic model using a Levy process to model the system's evolution. In addition, HepingLi et al. (2016) modeled this dependence using Levy copulas. They evaluated its influence on maintenance planning.

To the best of our knowledge, no prominent attention has been paid to the impact of the stochastic dependence on the integrated production planning and PM scheduling decisions. In this study, we consider a two components system where one component is stochastically dependent on the other. Consequently, assessing the stochastic dependence impact is performed by computing the dependence degree based on the failure history.

3. Problem Description

We consider a production system consisting of two components (denoted as C_1 and C_2) producing a unique product. The demand must be equal to the sum of the two component production rates during a given planning horizon H including T periods. Consequently, when the demand is high and the production rate of C_1 is insufficient, an additional demand is carried out on C_2. If C_2 fails, C_1should run at its maximum rate. However, a C_1failure stops the system immediately, whereas a C_2 failure only reduces the performance capacity of the system and accelerates its degradation (increase a C_1failure rate). C_2 can be considered as a subcontracting, a support, or a complementary component.
Components Failures occur following a known probability distribution with density function f_i (t). The time to repair is random according to a set of known probability distributions with density functions g_i (t). Each C_2 failure causes a random damage or accelerate a deterioration within C_1.
A PM policy is adopted to improve component availability. Planned preventive maintenance actions are permitted at the beginning of each maintenance period before the start of production activities. Whenever an unplanned machine failure occurs, a minimal repair (MR) is carried out. Each planning period $t \in H$ has a fixed length and is divided into S subperiods called maintenance periods.

To develop our approach, we present the following assumptions:

1) C_1 is considered as the main component and therefore it constitutes most of the system.
2) Failure probability distributions are known for all the components.
3) The components are assumed to produce the same product.
4) The components are repaired with a random time with a given distribution function.
5) C_1 after corrective interventions is as good as new (perfect maintenance).
6) C_2 after corrective interventions is as bad as old (minimal repair).
7) We consider that C_1 is stochastically depending on C_2.

4. Mathematical model

The objective is to formulate the available production capacity considering the stochastic dependence for a given period. In the following, the stochastic dependence is modeled according to the exponential distribution based on CPHM. Based on Bahou et al. (2021), the machine availability formulation is expressed as follows:

$$A_s = \frac{\int_0^{+\infty} R_0(t)^{\exp(\beta)}\, dt}{\int_0^{+\infty} R_0(t)^{\exp(\beta)}\, dt + MTTR_s} = \frac{\frac{1}{\lambda e^{\beta}}}{\frac{1}{\lambda e^{\beta}} + MTTR_s} \tag{1}$$

where λe^{β} is the failure rate considering the stochastic dependence effect.
When the components are independent (β = 0), the system availability A_s^0 is expressed as follows (canonical form):

$$A_s^0 = \frac{\frac{1}{\lambda}}{\frac{1}{\lambda} + MTTR_s} \tag{2}$$

For a given corrective and preventive maintenance costs. The expected maintenance cost during the planning horizon may vary respecting to the adopted maintenance policy and the excepted number of failures. In fact, the stochastic dependence effect increases the failure rate and can may the period replacement more frequently to improve the machine reliability. Therefore, cost increases as a function of the degree of this effect. Integrating production planning and preventive maintenance (PM) scheduling decisions aims to minimize the expected maintenance cost and the total production cost. Furthermore, making those decisions is restricted by various constraints such as constraints that relate inventory or backorder to the production and demand, constraints that limit the production of a specific period to avoid overproducing and overstocking, and constraints that ensure that the production does not exceed the available capacity production.

5. Results and Discussion

In the following, we summarize a set of numerical experiments to highlight the impact of β on the different costs. The system parameters are fixed as follows: Exponential (λ_1= 0 ,1), $MTTR_s = MTTR_1$ = 0,009 months. The nominal production rate g_1 equal to 30 items. The periodic demand, presented in Table 1 and Table 2, gives the holding, backorder, setup, and production costs. These costs are the same for all periods. As previously mentioned, C_1 is considered as the main component and therefore it constitutes most of the system. Therefore, the data and the obtained results are only concerns C_1.

Table 1. Demands

Period t	1	2	3	4	5	6	7	8
Demand	20	21	20	18	23	20	19	22

Table 2. Costs

Holding Cost ($)	Backorder cost ($)	Set-up cost ($)	Production cost ($)
10	30	700	50

Figures 1shows the effect of stochastic dependence on the production coast for different values of λ. We observe that this cost increases when β increases. Moreover, it illustrates that the impact of this dependence is more important when the failure rate is high, i. e. for the same degree of dependence, a production cost with a high failure rate is more important. It is explained by the fact that with an increase of the failure rate, the system availability is more and more degraded. Therefore, the system may not be able to generate inventory for protection against unplanned failure and it may not be able to satisfy the demand and thus, backorders are generated.

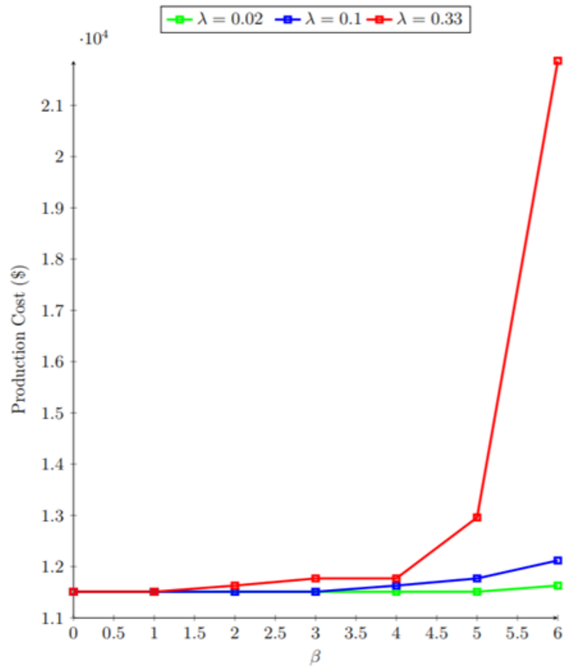

Figure 1. Impact of β on production cost with the variation of λ

Figure 2 reveals that the maintenance cost also increase with an increase of β. Its can be noticed that the cost registered is more impacted by this effect, which means that the stochastic dependence has a directly impact on the failure rate and the preventive maintenance plan. In one hand, an increase of failure rate generated an additional MR cost. In other hand, stochastic dependence makes PM period more frequent to mitigate its effect. Thus, an additional PM cost are caused.

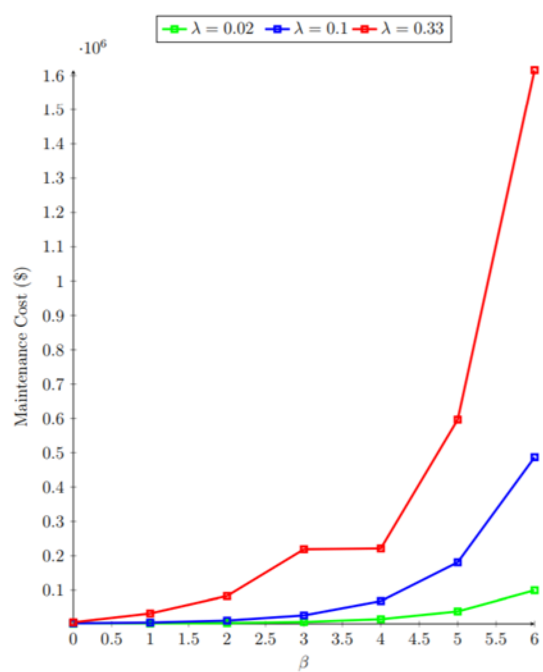

Figure 2. Impact of β on maintenance cost with the variation of λ

In figure 3, we can notice the impact of β on the available production capacity for different value of λ. Firstly, we observe that this figure supports the observations made in Figures 1 and 2. Secondly, we lost more available production capacity in function of β in systems with a higher failure rate, which means that the resistance to this effect is directly linked to the frequency of PM periods.

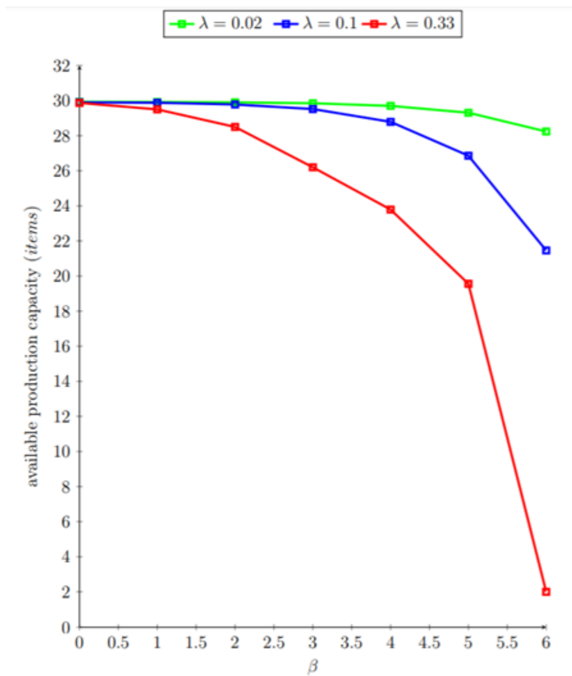

Figure 3. Impact of β on the available production capacity with the variation of λ

Based on the previous analysis, we highlight the following observations: (i) The available production capacity of system and costs are impacted significantly by the stochastic dependence; (ii) No considering the stochastic dependence effect during production planning and maintenance schedule causes excepted consequences and additional costs; (iii) The stochastic dependence has more impact on components that have a high probability of failure.

6. Conclusion

In this paper, we have evaluated the stochastic dependence effect on the integration of production planning and maintenance schedule for a parallel two-machine system. We proposed a new approach based on CPHM to incorporate the stochastic dependence on an integer linear program to determine the optimal production plan with preventive replacement. The results showed that the stochastic dependence effect significantly influences the production plans, maintenance policies, and costs. Hence, it is recommended to use such an approach as a starting point, to obtain a more realistic planning, because not considering the stochastic dependence effect during the planning of these two activities causes excepted consequences and additional costs.

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Biography

Nizar El Hachemi received his PhD in Operation Research from Polytechnic School of Montreal. Currently, he is a Professor at EMI. Recently, he was promoted to the rank of HDR. He developed hybrid solution methods for solving transportation problem encountered in forestry by taking advantage of constraint programming, constraint-based local search and linear integer programming. Recently, he has developed effective heuristic integrators for solving rich problems in collaboration with several researchers from the Interuniversity Research Centre on Enterprise Networks, Logistics and Transportation (CIRRELT).

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