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Joint production and human replacement optimization policy for a deteriorating manufacturing system

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ABSTRACT

This article examines the integration of production and human resource and human resource management, considering the operator as a production unit whose efficiency decreases over time, in an unreliable production system marked by significant deterioration. This deterioration impacts the reliability and continuity of the production unit in two main ways. To mitigate the impact of this deterioration, a replacement action can be implemented based on the system's current state. The objective of this study is to establish an effective production policy and replacement strategy to meet customer demand. We employ a combination of stochastic dynamic programming and numerical methods to solve this optimal control problem. Additionally, a numerical example is presented to demonstrate the applicability of the proposed approach and to explore the interaction between a specific production strategy and human resource management. The main contribution of this research lies in the development of innovative methods and solutions aimed at optimizing the performance of a complex system through stochastic optimal control. The impact of the new approach, based on a logical implementation, is discussed following a sensitivity analysis of the numerical example. The results include a comparative study between recent research and the proposed policy. Lastly, an implementation chart is created to assist decision-makers in determining production rates and managing human resources effectively to meet customer demand.

1. Introduction

Currently, in manufacturing, a revolutionary new step is about to be taken in the form of 'Industry 5.0', which places the emphasis on human involvement in the manufacturing system [1]. This industry is an evolution of industrial production that integrates humans and advanced technologies, combining the benefits of automation with human skills to create more efficient and flexible working environments. It thus gives rise to close collaboration between machines and workers, and enhances company productivity by optimizing production processes. This new generation of production systems combines human performance with the optimization of the entire production plant. While many controls strategy models have been proposed, they primarily focus on determining a joint optimization plan for production, quality, and both corrective and preventive maintenance. In this context, the human factor has often been neglected. However, since human intervention is essential during production, inspection, and maintenance activities, the reliability of the system depends largely on human reliability. Integrating this factor is crucial for optimizing the entire system, as the manufacturing model encompasses a production plant, resources (man and machine), and an evolving economic model that delivers competitively high-quality products. Consequently, many recent studies have shifted their focus to production control, quality, and maintenance planning policies that consider the human factor, which previously received insufficient attention. Previous studies have largely regarded humans as disruption factors within the system, focusing on their reliability [2], rather than viewing them as production units that degrade with age.

Since an unreliable operator reflects the overall availability of the system, this paper aims to contribute to the scientific literature by proposing an optimal production control and personnel replacement policy that considers the human factor as a manufacturing component that deteriorates randomly with age. The newly developed optimization approach minimizes total costs, which include shortage costs, inventory costs, and operator replacement costs. To effectively position our proposed integrated model, we provide an overview of recently published related research, which we categorize into three groups. The first category addresses the human factor and its role within the manufacturing system. The second focuses on production planning policies for deteriorating systems, while the third reviews replacement policies for systems subject to random downtime. To clarify the contributions of this work in relation to previous studies, Table 1 summarizes relevant articles based on key criteria related to unreliable manufacturing systems, human production rates, replacement policies, human performance, reliability, and optimal production control.

(i). In the manufacturing systems studied, humans are viewed as autonomous and intelligent production units. For this reason, most studies have explored two sub-factors: human reliability and its impact on the whole process and human error and its effects on industrial systems [3]. Other studies posit the human factor as the cause of accidents, quality defects and delays in industrial, aeronautical, automotive and hospital environments [4]. Moreover, Green and Senders [5] and Treat et al. [6] hold human error as the main cause in 57% of all accidents, and as a contributing factor in over 90% of them. In contrast, they attribute only 2.4% of accidents to mechanical defects, and 4.7% to environmental factors. Other studies show that despite the prominence of human error, humans still play a vital role in the system. Braganca et al. [3] explore the role humans play in modern, intelligent, and complex factories as part of Industry 4.0Based on the hypothesis that the human being is a complex system subject to random deterioration depending on age and effort, Nemeth [7] provides an in-depth practical guide to solving problems linked to human factors in the production process. However, multiple researchers, such as Baines et al. [8], Baines et al. [9] and Peruzzini and Pellicciani [10], have proposed an adaptive framework for human performance modeling in manufacturing systems design. Furthermore, the practice of personnel management is a human and organizational problem. Indeed, notwithstanding the effects of the human factor, its involvement is vital for industrial systems. Udo and Ebiefung [11] present an analysis of data collected from 98 manufacturing companies to investigate the associations between human factors and the success of advanced manufacturing systems. In the same context, research has been presented that demonstrates the importance of human involvement in systems as a whole. Examples include the work of Hoc et al. [12], who studied human scheduling skills and human operator factors in the production management of manufacturing workshops. Charba et al. [13] define the importance of human involvement in the success of quality management.

(ii). Given the growing competitiveness of industrial production systems, a variety of production optimization strategies for unreliable manufacturing systems have been proposed, each addressing different constraints. Most of the recent policies consider a constant and given demand rate. Rivera-Gómez et al. [14], Rivera-Gómez et al. [15], and Panda and Subrata [16] propose a policy to optimize the manufacturing rate of a seasonal perishable product given both a fixed and a variable demand during the sales season. Polotski et al. [17] propose a production policy for hybrid manufacturing systems subject to random deterioration under the constraint of a time-varying demand rate. The production of perishable products is considered to constitute the most complex manufacturing type in terms of management and planning. In this context, several related approaches have been proposed

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over the last three years. Polotski et al. [18] developed a production control policy for manufacturing systems for perishable products such as food and pharmaceutical and chemical goods. Gharbi et al [19] have developed a dynamic control scheme for unreliable systems with perishable products having variable shelf lives. Such a strategy aims to provide a production plan that constantly meets demand while remedying the effects of the deterioration of products that have been kept for too long in inventory. This subject has significant implications for both the environment and the economy of the manufacturing industries Production challenges are not the only factors that make manufacturing systems more complex. Imperfect maintenance has a clear influence on medium and long-term production plans. Each year, thousands of studies developing new optimization policies to address the problem of manufacturing system deterioration caused by minor and major imperfect repairs are proposed, such as that by Nodem et al. [20] and the references therein. Related studies here build on existing policies by appealing to the remanufacturing phenomenon, which designates the repair or remanufacture of the defective or returned product. Examples include Neng-H and Chih-h [21], Ouaret et al. [22] and Ouaret et al. [23], who propose a different production optimization strategy, which relies on the manufacture and remanufacture of the returned products. Their main purpose is to help managers make the best decisions regarding the control values related to production. Kibouka et al. [24] propose a production plan for a more complex system that undergoes repairs under different scenarios with changing product types on a single machine. Gharbi and Kenné [25] develop a production control policy for N numbers of units and M types of products, in the context of modern and complex systems.

(iii). Replacement policies for unreliable manufacturing systems deal with one or more parts being replaced in the machine after a predefined time. Wakiru et al. [26] explains that the implementation of such a strategy usually depends on the history of minor repairs and a predefined time interval of the parts' lifetime. Nodem et al. [27] demonstrate that in critical failure situations, the option of replacing the entire machine with a new one can be chosen, and carries a lower total cost as compared to a partial repair. Indeed, several studies state that over time, a machine that has undergone a number of imperfect repairs must be replaced. In this context, Zeng and Zhou [28] and Ouaret et al. [29] propose a replacement policy for a production system by determining the optimal replacement rate that minimizes the total cost of the studied system. In addition, Ouaret et al. [23] have demonstrated that with quality degradation as well as a variable demand rate, the option of replacing the machine must be chosen to eliminate the effects of aging on product defects, while allowing demand to be met in the long term. Ouaret et al. [30] studied a manufacturing system undergoing increasing deterioration of its production rate, where an age-dependent replacement action was undertaken following imperfect repairs that had led to the aging of the machine. In a different context, Lai et al. [31], proposed a replacement policy for a production unit where the production unit causes a certain damage to the items by increasing the latter's failure rate. Many replacement strategies for a part or a production unit have recently been proposed under different constraints of quality, age and imperfect repairs.

Table 1. Summary of the contributions of different authors

Articles	manufacturing system	Optimal production control	Replacement rate control	Human performance and reliability	Human production rate
i- Human manufacturing system					
[2]	√	√		√	
[10]	√			√	
[11]	√	√		√	
[8]	√	√		√	
[9]	√	√		√	√
[14]	√	√		√	
[4]	√			√	
[5]	√			√	
[6]	√			√	
[3]	√			√	
[7]	√			√	

Articles	manufacturing system	Optimal production control	Replacement rate control	Human performance and reliability	Human production rate
ii- Production planning policies					
[14]	√	√			
[15]	√	√			
[16]	√	√			
[17]	√	√			
[22]	√	√			
[19]	√	√			
[25]	√	√			
[18]	√	√			
[20]	√	√			
[24]	√	√			
iii- Replacement strategies for unreliable systems					
[26]	√	√	√		
[31]	√	√	√		
[23]	√	√	√		
[22]	√	√	√		
[30]	√	√	√		
[29]	√	√	√		
Our study	√	√	√	√	√

Based on the literature and Table 1, a key finding from the previously discussed studies is that none address the combined impact of deterioration and uncertainties on a manufacturing system that incorporates human elements into the production process. Furthermore, the interactions between production and replacement strategies are overlooked, representing a significant gap, particularly in contexts involving human factors. The primary contribution of this paper is the integrated optimization of production and replacement control for an unreliable manufacturing system subject to deterioration and uncertainties. The specific contributions of this research can be outlined as follows:

- Development of an optimization model to determine the optimal production and replacement policy structures in a dynamic and stochastic production context.
- Development of a decision support tool for managers in a manufacturing production context integrating the human factor into the production process.

The methodology adopted in this research relies on a modeling approach based on stochastic optimal control theory appropriate to discrete state optimization problems as in the work of Ouaret et al. [23]. The structure of the control policy (production and replacement rates) will be obtained using the fact that the value function is the unique solution of the Hamilton-Jacobi-Bellman (HJB) equations describing the optimum of the control problem formulated. Then, under suitable conditions, an algorithm is implemented to numerically solve the optimal conditions using a numerical example. This helps define the policy structure and demonstrates the effectiveness of the proposed method.

This paper is organized as follows. In section 2, we present the method adopted including the notations, assumptions, problem statement, numerical approach and optimal control policy. Section 3 is dedicated to resultants and discussion based on a sensitivity analysis, a comparative study and managerial implementations. Finally, in section 4, we conclude this study and offer some guidelines for further research.

2. Method

The following are the notations adopted in this paper:

$(\boldsymbol{t})$: Stochastic process of human reliability

$\boldsymbol{x}_2(\boldsymbol{t})$: Stock level at time $\boldsymbol{t}$

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$\boldsymbol{x}_1(\boldsymbol{t})$	: Production age of the operator at time $\boldsymbol{t}$
$\boldsymbol{d}$	: Demand rate
$\boldsymbol{\alpha}(\boldsymbol{t})$	: State of the operator at time $\boldsymbol{t}$
$\boldsymbol{U}_{\boldsymbol{max}}$	: Maximum production rate at state $\boldsymbol{t}$
$\boldsymbol{\beta}(\boldsymbol{t})$	: Rejection rate
$\boldsymbol{w}(.)$	: Rate of replacement of operator
$\boldsymbol{C}_{\boldsymbol{remp}}$	: Cost of replacement of operator
$\boldsymbol{C}^{+}$	: Inventory cost
$\boldsymbol{C}^{-}$	: Shortage cost
$\boldsymbol{C}_{\boldsymbol{r}1}$	: Cost of sending the operator to rest at state 2
$\boldsymbol{C}_{\boldsymbol{r}2}$	: Cost of sending the operator to rest at state 3
$\boldsymbol{q}_{\boldsymbol{ij}}$	: Transition rate from mode i to mode j, with $i, j \epsilon \{1,2,3,4,5\}$
$\boldsymbol{Q}(.)$	: Transition rate matrix
$\boldsymbol{g}(.)$	: Instantaneous cost function
$\boldsymbol{J}(.)$	: Total cost function
$\boldsymbol{V}(.)$	: Value function

The assumptions of the study are as follows:

- The raw material is always available for the production unit.
- The demand rate is constant and known during all time periods.
- The level of deterioration of the operator is defined by their age.
- Upon system failure, a rest period is taken, leaving the operator in an as-bad-as-old condition.
- A replacement action implies a perfect option to restore the process to an as-good-as-new condition.
- The machine is assumed to be reliable and available during all time periods.
- The operator’s rest rates are constant and known.
- The breakage rate, storage, rejects and returns costs are known for each product.

Our aim is to build upon and further the extend existing models. This paper considers the case of a continuous flow manufacturing system subject to deterioration. It consists of a human operator, producing one type of products and feeding the finished goods inventory to meet a constant demand over an infinite horizon, such as presented in Fig. 1 representing an aggregate production system that can be extended to any manufacturing industry operating within the scope of the hypotheses of this research.

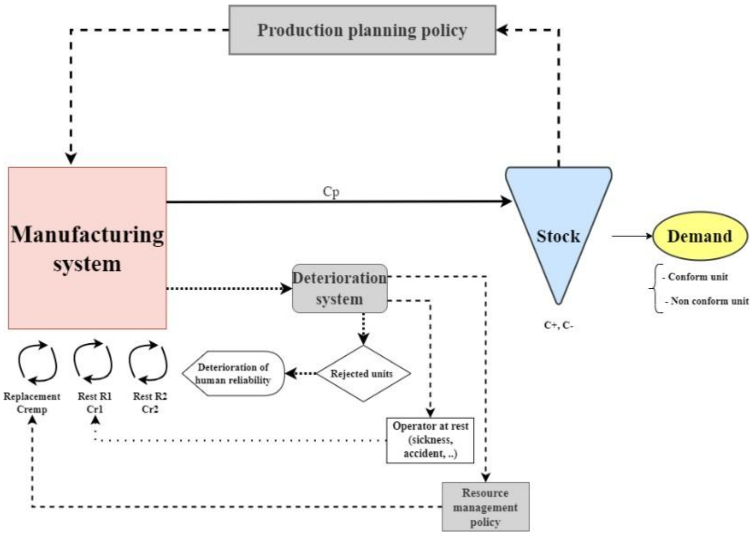

Fig. 1. Production system under study

The proposed model consists of an unreliable manufacturing system incorporating the human factor in the form of a machine operator, and producing one type of product, and which is subject to random shutdowns and age-dependent deterioration. The manufacturing system's mode at time t is given by the random system $\zeta(t)$, with $B = \{1,2,3,4,5\}$, when $\zeta(t) = 1$ means the system is operational with zero rejected items. When $\zeta(t) = 2$, the operator is experiencing sudden failure caused by an accident, illness or physical defect that appeared at time t. In this case, the operator will be returned to rest R1 for recovery or correction. When the operator's reliability gradually decreases due to fatigue, or has reached maximum work capacity or is facing unfavorable environmental conditions, the system goes to state $\zeta(t) = 3$, where the operator is in operation with an increasing rejection rate depending on age. At $\zeta(t) = 4$, the operator is in R2 rest, allowing it to recover some of its reliability. When $\zeta(t) = 5$, operator replacement is conducted to restore the system to its initial state. The system is likely to be in a closed loop between states 3 and 4, until the production system reaches a comfortable inventory level with high age.

The modes of the production system are given by the following process:

$$\zeta(t) = \begin{cases} 1 & Operator\ in\ operation \\ 2 & Operator\ at\ rest\ R1 \\ 3 & operator\ in\ operation\ producing\ rejects \\ 4 & Operator\ at\ rest\ R2 \\ 5 & Operator\ at\ remplacement \end{cases} \quad (1)$$

The transition diagram of this stochastic process is shown in Fig. 2

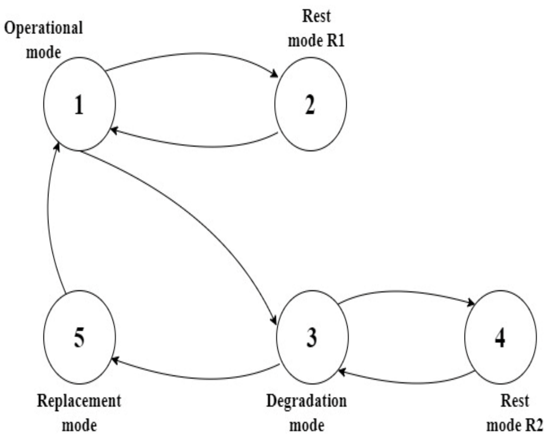

Fig. 2. Transition diagram

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The stochastic process is described by the transition matrix $Q(.) = [q_{ij}]$, where q_{ij} agrees with the following conditions:

$$q_{ij} \geq 0 \qquad (i \neq j), \tag{2}$$

$$q_{ii} = -\sum_{i \neq j} q_{ij} \tag{3}$$

The transition probabilities are given by:

$$P[\zeta(t+1) = j | \zeta(t) = i] = \begin{cases} q_{ij}(.)\delta t + o(\delta t) & if \;\; i \neq j \\ 1 + q_{ij}(.)\delta t + o(\delta t) & if \;\; i = j \end{cases} \tag{4}$$

where $\lim_{\delta \to 0} \frac{o(\delta t)}{\delta t} = 0$ for all $\forall i, j \in B$ et $i \neq j$

The age of the production system is given by the following equation:

$$\frac{dx_1(t)}{dt} = ku(t) \tag{5}$$

$$x_1(.) = 0 \tag{6}$$

where k is a positive constant. The transition matrix $Q(.)$ represented in equation (7) of the stochastic process $\zeta(t)$ depends on the age and on the replacement rate. To resolve the effects of deterioration, we introduce the control value $w(.) \in \{w_{min}, w_{max}\}$, where $w(.)$ is positioned at its maximum value w_{max} if a replacement action was made and at w_{min} otherwis.

$$(.) = \begin{pmatrix} q_{11} & q_{12}(x_1) & q_{13}(x_1) & 0 & 0 \\ q_{21} & q_{22} & 0 & 0 & 0 \\ 0 & 0 & q_{33} & q_{34} & q_{35}(.) \\ 0 & 0 & q_{43} & q_{44} & 0 \\ q_{51} & 0 & 0 & 0 & q_{55} \end{pmatrix} \tag{7}$$

It is obvious that the deterioration of the operator can mostly be attributed to the age factor, which also has an impact on the interruption rate, q_{12}, which represents an increasing function of age [30], described as follows:

$$q_{12}(x_1) = \mu_0 + \mu_1 * (1 - e^{-\mu_2 * [x_1(t)^3]}) \tag{8}$$

where μ_0, μ_1 and μ_2 are constant. The trend of the interruption rate for the different values of μ_2 is presented in Fig. 3. There, we can see a significant influence of the operator deterioration on the interruption rate, since q_{12} increases proportionally to the operator's age. However, the deterioration impacts not only the shutdown rate, but also the human reliability, which in turn leads to an increasingly high rejection rate for the produced goods. Thus, the transition rate of degradation is an increasing function of age, as denoted by the following equation:

$$q_{13}(x_1) = n_0 + n_1 * (1 - e^{-n_2 * [x_1(t)^3]}) \tag{9}$$

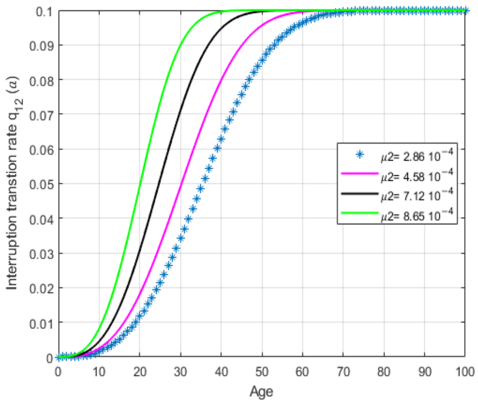

Fig. 3. Variation of interruption transition rate according to age

where n_0, n_1 and n_2 are constants, Fig. 4 represents the human performance deterioration trend for different values of the n_2 parameter, and illustrates the influence of deterioration on human performance in the production system.

We note that both Eq.(8) and Eq. (9) describe two different phenomena, namely, human performance and human reliability. Human performance defines one's ability to work without any interruption (e.g., due to illness), while on the other hand, human reliability defines the operator's ability to operate without producing rejects or defects.

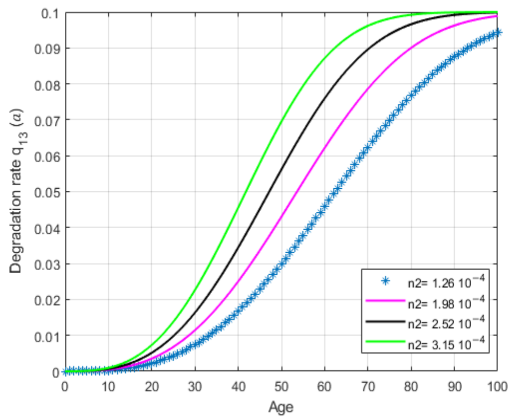

Fig. 4. Variation of degradation transition rate as a function of age

In theory, the degradation of human reliability in the production process can be translated by an increase in the percentage of rejection as a function of age. Thus, the rejection rate is an increasing function of age described by Eq. (10), which demonstrates the influence of age on the rejection rate $\beta(x_1)$, as illustrated in Fig. 5.

$$\beta(x_1) = v_0 + v_1 * (1 - e^{-v_2*[x_1(t)^3]}) \qquad (10)$$

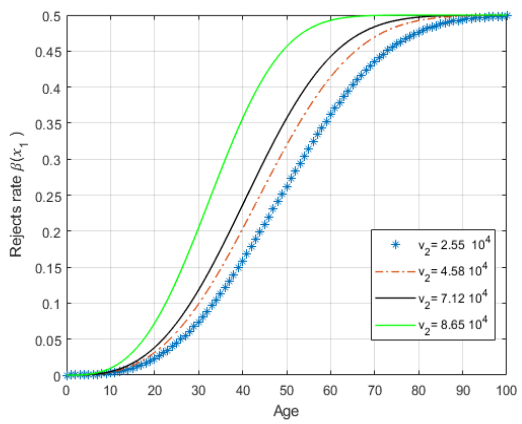

Fig. 5. Variation of rejection rate according to age

The more the human reliability deteriorates, the more the number of rejections increases. Consequently, the production capacity decreases, which in turn affects the dynamics of the stock. The inventory level is given by:

$$\dot{x}_2(t) = [1 - \gamma(x_1, \alpha)] * u(t) - d, \qquad x_2(0) = x_2 \qquad (11)$$

where $u(t)$ represents the production rate and d is the customer demand rate (which is assumed to be fixed and constant). $\gamma(x_1, \alpha)$ is the rejection rate as a function of age at state α, which is defined as follows:

$$\gamma(x_1, \alpha) = \begin{cases} \beta(x_1) & if \;\; \alpha = 4 \\ 0 & otherwise \end{cases} \qquad (12)$$

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The objective of our model is to determine the production rate $u(.)$ when the operator is in operation mode 1 and in degradation mode 3, as well as the replacement rate $w(.)$

The feasibility domain, including $u(.)$ and $w(.)$ is given by:

$$\psi(\alpha) = \{(u(.), w_r(.) \in \mathbb{R}^2, 0 \le u(.) \le u_{max}, w^{min} \le w(.) \le w^{max} \tag{13}$$

The cost function is presented as:

$$g(\alpha, x_1, x_2, u, w) = C^+ x_2^+ + C^- x_2^+ + C_{remp}.Ind\{\alpha = 5\} + C^\alpha, \quad \forall\alpha \in B \tag{14}$$

Where:

$$C^\alpha = \begin{cases} C_{r1} & if\ \alpha = 2 \\ C_{r2} & if\ \alpha = 4 \end{cases} \tag{15}$$

$$Ind(\alpha) = \begin{cases} 1 & if\ \zeta(t) = \alpha \\ 0 & Otherwise \end{cases} \tag{16}$$

with C_{remp} being the cost of replacing the operator. On the other hand, C^+ and $C^-$are the inventory and shortage costs, respectively. The idle cost in mode 2 is denoted by C_{r1}, while that in mode 4 is denoted by C_{r2}.

As mentioned before, the objective of the proposed model is to find the optimal control policy in $\psi(\alpha)$ that minimizes the following value function:

$$v(x_2, x_1, \alpha) = \min_{u,w \in \psi(\alpha)} J(\alpha, x_1, x_2, u, w), \quad \forall\alpha \in B \tag{17}$$

Where: ρ is the positive discount rate

$$J(\alpha, x_2, x_1, u, w) = E\{\int_0^\infty e^{-\rho t} g\,(x_2, x_1, u, w)dt | x_2(0) = 0, x_1(0) = 0\} \tag{18}$$

For the determination of the optimal controls ($u(.)$ and $w(.)$), we refer the reader to Ouaret et al. [29] for the replacement rate, and to Kenné and Nkeungoue [32] for the production rate. These authors demonstrate that the value function defined in Eq. (17) is strictly convex in (x_2, x_1).

The properties of the value function $v(.)$ can be found in Rivera-Gomes et al. [14], [15] where $\dot{x}_2$ and $\dot{x}_1$ are replaced by both Eq. (11) and Eq. (5) respectively, to obtain the value function $v(x_2, x_1, \alpha)$, which is the solution to the HJB function defined as follows:

$$\rho v(\alpha, x_2, x_1) = \begin{bmatrix} g(x_2, x_1, u, w) + v_{x_2}(.)([1 - \gamma(x_1, \alpha)] * u(t) - d) + ku(t)v_{x_1}(.) \\ + \sum_{\beta \in B} q_{ij}(.)[v(\alpha, x_2, \xi(x_1, \zeta)) - v(\alpha, x_1, x_2)] \end{bmatrix} \tag{19}$$

Here, $v_{x_2}$and v_{x_1} denote the partial derivatives of the value function $v(\alpha, x_2, x_1)$. Finding an analytical solution for equation (19) is typically quite challenging. Instead, it can be approximated using numerical methods inspired by Kushner's approach [33], [34]. Let us now present a numerical example to demonstrate the proposed method based on Kushner's approach [33] in order to develop a numerical method that solves the optimal conditions just presented above. The goal of this approach is to apply a gradient approximation scheme to the value function $v(\alpha, x_1, x_2)$. h_{x_1} and h_{x_2} represent the finite lengths of the intervals of values x_1 and x_2, respectively, as in Kenné and Nkeungoue [32] and in the references therein.

Using h_{x_2}, $v(x_2, \alpha)$ is approximated by $v^h(x_1, x_2, \alpha)$ and $v_{x_2}(x_1, x_2, \alpha)$ is approximated as in the following equation:

$$v_{x_2}(x_1, x_2, \alpha).\dot{x}_2(t) = \begin{Bmatrix} \frac{1}{h_{x_2}}\left(v^h(\alpha, x_2 + h_{x_2}, x_1) - v^h(\alpha, x_2, x_1)\right) \times \dot{x}_2(t) & if\ \dot{x}_2(t) > 0 \\ \frac{1}{h_{x_2}}\left(v^h(\alpha, x_2, x_1) - v^h(\alpha, x_2 - h_{x_2}, x_1)\right) \times \dot{x}_2(t) & otherwise \end{Bmatrix} \tag{20}$$

Using $h_{x_1}, v_{x_1}(x_1, x_2, \alpha)$ is approximated as in the following equation:

$$v_{x_1}(x_1, x_2, \alpha).\dot{x_1}(t) = \frac{1}{h_{x_1}}\left(v^h(\alpha, x_1, x_1 + h_{x_1}) - v^h(\alpha, x_2, x_1)\right) \times \dot{x_1}(t) \quad (21)$$

Using approximation equations (20) and (21), and after a couple of manipulations, the HJB equation can be rewritten in the following form:

$$v^h(\alpha, x_2, x_1) = \min_{u, w_r \in \psi(\alpha)} \left\{ \frac{c^+ s^+ + c^- s^-}{\Omega_h^\alpha (1 + \frac{\rho}{\Omega_h^\alpha})} + \frac{1}{\Omega_h^\alpha \left(1 + \frac{\rho}{\Omega_h^\alpha}\right)} \begin{pmatrix} p_{x_2}^\pm(\alpha) v^h(\alpha, x_2 \pm h_{x_2}, x_1) \\ + p_{x_1}(\alpha) v^h(\alpha, x_2, x_1 - h_{x_1}) + \sum_{\beta \neq \forall \alpha} p^\beta(\alpha) v^h(\alpha, x_2, x_1) \end{pmatrix} \right\} \quad (22)$$

The terms used in equation (22) are defined as follows:

$$\Omega_h^\alpha = \left|q_{ij}\right| + \frac{|([1-\gamma(x_1,\alpha)] * u(t)) - d|}{h_{x_2}}$$

$$p_{x_2}^+(\alpha) = \begin{cases} \frac{([1-\gamma(x_1,\alpha)] * u(t)) - d}{h_{x_2} \Omega_h^\alpha}, & if\ [1 - \gamma(x_1, \alpha)] * u(t) - d > 0 \\ 0 & otherwise \end{cases}$$

$$p_{x_2}^-(\alpha) = \begin{cases} \frac{d - ([1-\gamma(x_1,\alpha)] * u(t))}{h_{x_2} \Omega_h^\alpha} & if\ d - ([1 - \gamma(x_1, \alpha)] * u(t)) < 0 \\ 0 & otherwise \end{cases}$$

$$p_{x_1}(\alpha) = \frac{ku(t)}{h_{x_1} \Omega_h^\alpha}$$

$$p^\beta(\alpha) = \frac{q_{ij}}{\Omega_h^\alpha}$$

noting that $p_{x_2}^+(\alpha) + p_{x_2}^-(\alpha) + p_{x_1}(\alpha) + \sum_{\beta \neq \alpha} p^\beta(\alpha) = 1$, the terms $p_{x_2}^+(\alpha), p_{x_2}^-(\alpha), p_{x_1}(\alpha)$, and $p^\beta(\alpha)$, for all $\beta \neq \alpha$, can be considered as transition probabilities for a controlled Markov chain. The reader is referred to Kenné and Nkeungoue [32] for details on these theorems.

For the rest of this paper, we present a numerical example of the system explored in section 5. The system capacity is described by 5 states of the Markov process, with $B = \{1,2,3,4,5\}$. The generating matrix described by Eq. (7) is defined as follows:

$$Q(.) = \begin{pmatrix} -(q_{12}(x_1) + q_{13}(x_1)) & q_{12}(x_1) & q_{13}(x_1) & 0 & 0 \\ q_{21} & -q_{21} & 0 & 0 & 0 \\ 0 & 0 & -(q_{34} + W(.)) & q_{34} & W(.) \\ 0 & 0 & q_{34} & -q_{34} & 0 \\ q_{51} & 0 & 0 & 0 & -q_{51} \end{pmatrix} \quad (23)$$

Where $q_{12}(x_1)$ and $q_{14}(x_1)$ are described by both Eq. (8) and Eq. (9), respectively.

To study the robust interaction between production planning and human resource management, a complex mathematical structure is conducted. Rivera-Gomez et al. [15] and Garbi et al. [19] show that such a problem is solved by a discrete version of the dynamic programming equation HJB Eq. (19). Thus, we obtain the following five equations.

$$v^h(1, x_1, x_2) = \min_{u \in \psi(1)} \left\{ \frac{c^+ x_2^+ + c^- x_2^+}{(1 + \rho/\Omega_h^1)} + \frac{1}{(1 + \rho/\Omega_h^1)} \left(p_{x_2}^\pm(1) v^1(1, x_2 \pm h_{x_2}, x_1) + p_a(1) v^1(1, x_2, x_1 + h_{x_1}) + p^2(1) v^1(2, x_1, x_2) + p^4(1) v^1(4, x_1, x_2) \right) \right\} \quad (24)$$

$$v^h(2,x_1,x_2) = \min_{\psi(2)} \left\{ \begin{array}{c} \frac{C^+x_2^+ + C^-x_2^+ + C_{r1}}{\left(1+\frac{\rho}{\Omega_h^1}\right)} + \\ \frac{1}{(1+\rho/\Omega_h^1)}\left(p_{x_2}^-(2)v^2(2,x_2-h_x,x_1) + p_{x_1}(2)v^2(2,x_2,0) + p^1(2)v^2(2,x_1,x_2)\right) \end{array} \right\} \quad (25)$$

$$v^h(3,x_1,x_2) = \min_{u\in\psi(3)} \left\{ \frac{C^+x_2^+ + C^-x_2^+ + C_{r1}}{(1+\rho/\Omega_h^1)} + \frac{1}{(1+\rho/\Omega_h^1)}\left(p_{x_2}^{\pm}(3)v^h(1,x_2 \pm h_{x_2},x_1) + p_{x_1}(3)v^h(3,x_2,x_1+h_{x_1}) + p^3(3)v^h(5,x_1,x_2) + p^5(3)v^h(4,x_1,x_2)\right)\right\} \quad (26)$$

$$v^h(4,x_1,x_2) = \min_{\psi(4)} \left\{ \begin{array}{c} \frac{C^+x_2^+ + C^-x_2^+ + C_{r2}}{\left(1+\frac{\rho}{\Omega_h^1}\right)} + \\ \frac{1}{(1+\rho/\Omega_h^1)}\left(p_{x_2}^-(4)v^h(1,x_2-h_{x_2},x_1) + p_{x_1}(4)v^h(4,x_2,0) + p^4(4)v^h(3,x_1,x_2)\right) \end{array} \right\} \quad (27)$$

$$v^h(5,x_1,x_2) = \min_{w\in\psi(5)} \left\{ \begin{array}{c} \frac{C^+x_2^+ + C^-x_2^+ + C_{remp}}{\left(1+\frac{\rho}{\Omega_h^1}\right)} + \\ \frac{1}{(1+\rho/\Omega_h^1)}\left(p_{x_2}^-(5)v^h(1,x_2-h_{x_2},x_1) + p_{x_1}(5)v^h(5,x_2,0) + p^1(5)v^h(1,x_1,x_2)\right) \end{array} \right\} \quad (28)$$

Let θ denoting the state variables (x_1, x_2) described by:

$$\theta = \{(x_1,x_2): -50 < x_2 < 50; 0 < x_1 < 100\} \quad (29)$$

We recall that the interruption, degradation, and rejection rates depend on the age of the operator described in equations (8), (9) and (10) respectively.

The intervals denoted in expression (29) are needed in the numerical technique. The limiting probabilities of the modes $\zeta(t) \in B$ (i.e., π_1, π_2, π_3, π_4 et π_5) can be calculated as follows:

$$\begin{cases} \pi_y . Q(.) = 0 \\ \sum_{y=1}^{5} \pi_y \end{cases} \quad (30)$$

where $Q(.)$ is the transition rate matrix given by Eq.(23). For reasons of consistency, we should ensure that the production system is able to meet customer demand in case of high deterioration, and must therefore satisfy the following feasibility conditions.

$$\begin{cases} \pi_y . U_{max} \geq d \quad if \;\; y = 1 \\ \pi_y . [(1-\beta(x_1)) \times U_{max}] \geq d \quad if \;\; y = 4 \end{cases} \quad (31)$$

where π_y is the bounded probability of the operational mode $y = 1$ and the operational mode with degradation $y = 3$. Table 2 showcases the parameters used in the numerical example and the cost parameters are presented in Table 3.

Table 2. Parameters of the numerical example (basic case)

q_{21}	q_{45}	w^{min}	w^{max}	q_{31}	$U1_{max}$	$U2_{max}$	d	h_{x1}	h_{x2}	x1-sup
0.05	0.001	10^{-7}	0.2	0.2	0.85	0.85	0.7	0.5	0.5	40
x1-inf	**x2-sup**	**x2-inf**	ρ	q_{54}	k_0	k_1	k_2	v_0	v_1	v_2
0	50	-50	0.1	0.5	1	0.1	10^{-7}	1	0.1	10^{-7}

q_{21}	q_{45}	w^{min}	w^{max}	q_{31}	$U1_{max}$	$U2_{max}$	d	h_{x1}	h_{x2}	x1-sup
b_0	b_1	b_2								
0.001	0.5	10^{-7}								

Table 3. Cost parameters of the numerical example

c^+	c^-	c_{r1}/c_{r2}	c_{remp}
5	20	5	50

For the first controlled variable $u(.)$, Fig. 6, Fig. 7 and Fig. 8 show that it is unnecessary to produce parts when the inventory level reach the threshold Z. It is interesting to note that the zone where the production rate is set at zero corresponds to the zone where the stock level is higher than the production threshold and where the age of the operator is high. On the other hand, the zone where the production rate is set to its maximum is developed when the inventory level drops below the production threshold. This is illustrated by the fact that $u(1{,}8{,}0) = 0$ or $u(1{,}8{,}45) = U_{max}$ (i.e., in mode 1, when the stock level is 8 and the operator's age is 0, the production rate is set to zero and if the stock level is 8 and the operator's age is 45, the production rate is set to the maximum value) and $u(3{,}27{,}0) = 0$ ou $u(3{,}27{,}60) = U_{max}$ (i.e., in mode 3, when the stock level is 27 and the age of the operator is 0, the production rate is fixed at zero and if the stock level is 27 and the age of the operator is 60, the production rate is fixed at the maximum value). Thus, when the operator is in deterioration (mode 3), the safety stock level is higher than it is when the operator is in operational mode (mode 1). In other words, the proposed policy considers the rejection rate $\beta(x_1)$, which is proportional to the age of the operator.

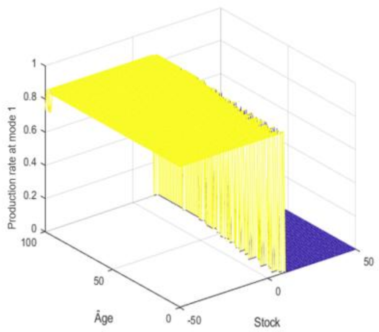

Fig. 6. Operator production rate at mode 1

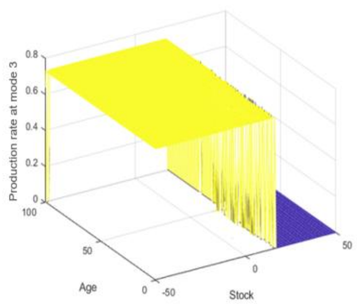

Fig. 7. Operator production rate at mode 3

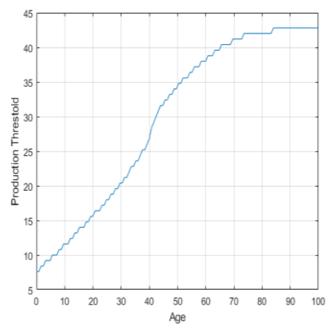

Fig. 8. Production trace versus age of the operator

The production policy comprises three regions, each governed by the following rules:

- Set the operator's production rate to its maximum value when the existing stock level is below the age-dependent threshold value.
- Set the operator's production rate to the demand rate when the current stock level equals the age-dependent threshold value.
- Set the operator's production rate to zero when the current stock level is well above the age-dependent threshold value.

Thus, the production policy is given by the following equations:

$$u(x_2, x_1, 1) = \begin{cases} U_{max} & if x_2 < f(.), \\ d & if x_2 = f(.), \\ 0 & otherwise, \end{cases} \quad (32)$$

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$$u(x_2, x_1, 3) = \begin{cases} (1-\beta(x_1)) \times U_{max} & if x_2 < f(.), \\ d & if x_2 = f(.), \\ 0 & otherwise, \end{cases} \tag{33}$$

The age-dependent function $f(x_1)$ is defined by the following equation:

$$f(x_1(t)) = \begin{cases} A^*(x_1) & if \;\; x_1(t) = \lambda^*(x_1) \\ 0 & Otherwise \end{cases} \tag{34}$$

where $A^*$is the critical age and λ^* is the optimal value of the dependent age.

The rate of the operator's replacement $w(.)$ is shown in Fig. 9. The domain (x_2, x_1) is divided into two regions where the replacement rate is set to its maximum value for a critical situation, and it is set to zero when the stock level is lower than the threshold value. However, the optimal replacement policy is based on the age of the operator and on the existing inventory level.

In our case, the critical situation is determined when the age of the operator is very high, with a stock level lower than the threshold production value. In this situation, the production system is deteriorating and its priority is to meet the demand. It is then necessary to replace the operator and return the system to its initial operating state, as presented in Fig. 9.

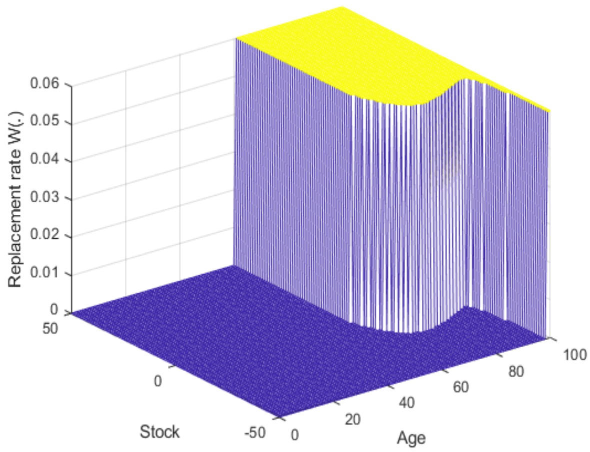


Fig. 9. Operator replacement rate at mode 5

The replacement policy plan is represented by the following function:

$$w(x_2, x_1, 3) = \begin{cases} w^{max} & if \;\; x_2(t) < X^*(x_1), \\ w^{min} & otherwise, \end{cases} \tag{35}$$

As described by Kenné and Nkeungoue [32], $X^*(x_1)$ represents the age-dependent function that gives the optimal stock level where the replacement mode must be changed from w^{min} to w^{max} for a given operator age.

3. Results and Discussion

Sensitivity analysis. Let us examine the joint optimal policy obtained earlier, where we analyzed the effect of varying the cost parameters in Table 2 relative to the production policy $u(.)$ and replacement policy $w(.)$. The parameters considered in the present analysis are the inventory cost, shortage cost, and replacement cost.

Variation of the backlog cost. The findings displayed in Fig. 10 correspond to three distinct values of $\boldsymbol{C}^- = 100, 200$ and 500 indicate that when the shortage cost increases, the inventory level increases significantly. Because the production threshold must be increased to meet demand and avoid high shortage costs, the operator will produce for a longer amount of time at the maximum rate. In this context, human reliability deteriorates faster, and therefore, the replacement rate of the operator will increase.

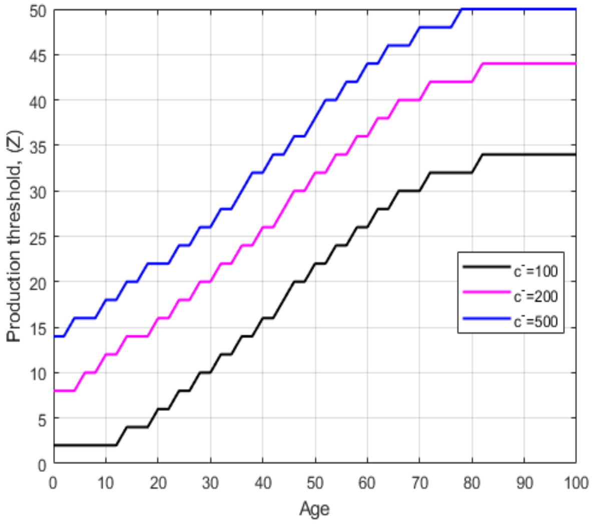
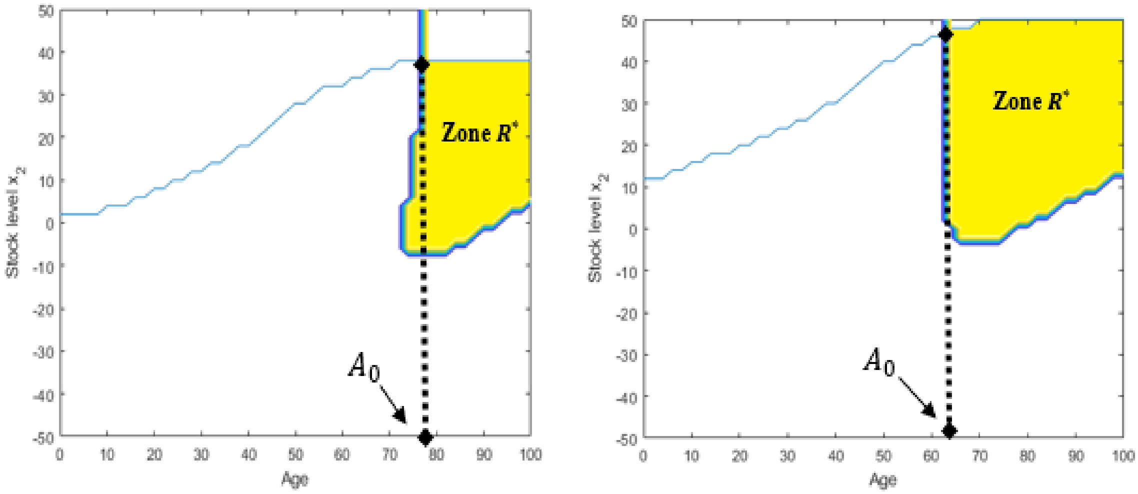


Fig. 10. Impact of backlog cost on the production control policy

We observe in Fig. 11 that with the increase in the shortage cost, the R^*zone becomes wider and the critical age A_0 that triggers a replacement is reduced. It is thus necessary to replace the operator earlier, with a higher optimal stock level, in order to restore the system to its initial condition and mitigate any deterioration effects on the production system and on the total cost.



a) - $C^- = 100$ **b) -** $C^- = 500$

Fig. 11. Impact of backlog cost on the replacement control policy

Variation of the inventory cost. For the three varying values of inventory costs, $\boldsymbol{C^+} = 3, 11$ and 21, The results indicate that as the inventory cost rises, the inventory level decreases considerably. Then, the threshold production value must be reduced to avoid surplus costs. Consequently, the operator's production will be fixed at current demand over a long period. The replacement rate is reduced considerably, as shown in Fig. 12.

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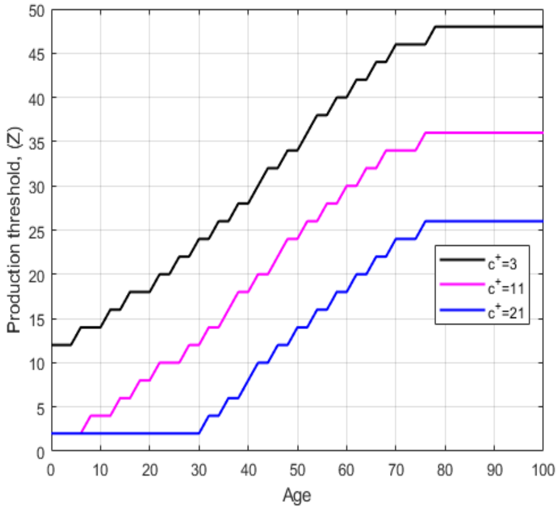
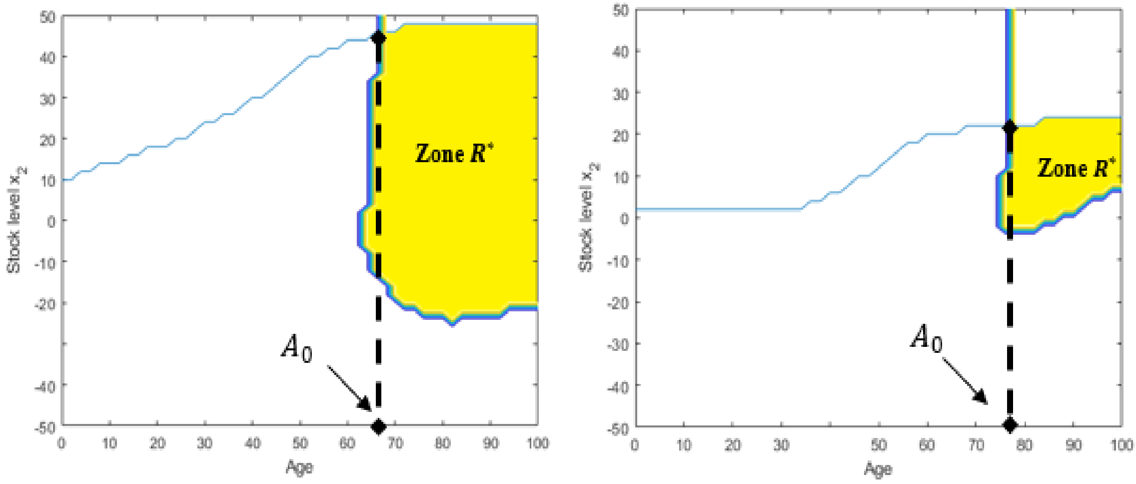


Fig. 12. Effect of inventory cost on the production control policy

Regarding the effect of the variation of the inventory cost on the replacement rate, as presented in Fig. 13, we note that with the variation of the inventory cost, the area R^* becomes smaller and smaller, and the critical age A_0 increases. It is thus clear that the operator should be replaced later, with a lower optimal inventory level. We also see that the variation of the inventory cost has an opposite effect from the variation of the shortage cost in the control policy studied.



a) - $C^+ = 3$ b) - $C^+ = 21$

Fig. 13. Impact of inventory cost on the replacement control policy

Variation of the replacement cost. We note in Fig. 14, for the three replacement cost values $C_{remp} = 100, 200$, that as the replacement cost increases, the production threshold value decreases. Consequently, the production rate needs to be lowered to prevent rapid deterioration of reliability and to maintain system operation for a longer duration. This results in a very low operator replacement rate, enabling the system to meet only the demand. Looking at the variation of the replacement cost, we can see that it has a similar effect as the inventory rate on the system control policy. Therefore, it is recommended that the system produce just the demand in order to remain reliable for longer and to reduce the replacement rate, which decreases costs.

It is noted that the variation of the replacement cost has the same effect as the variation of the inventory cost on the control policy studied (see Fig. 15).

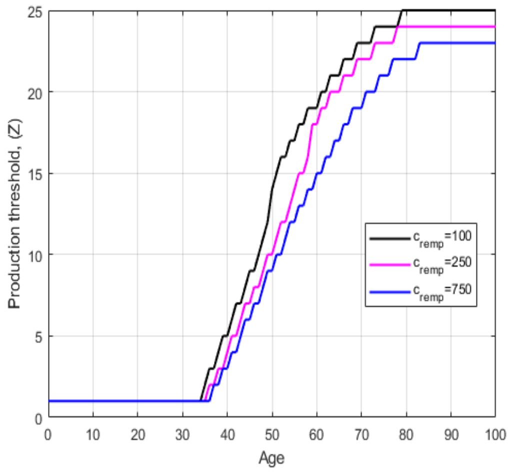
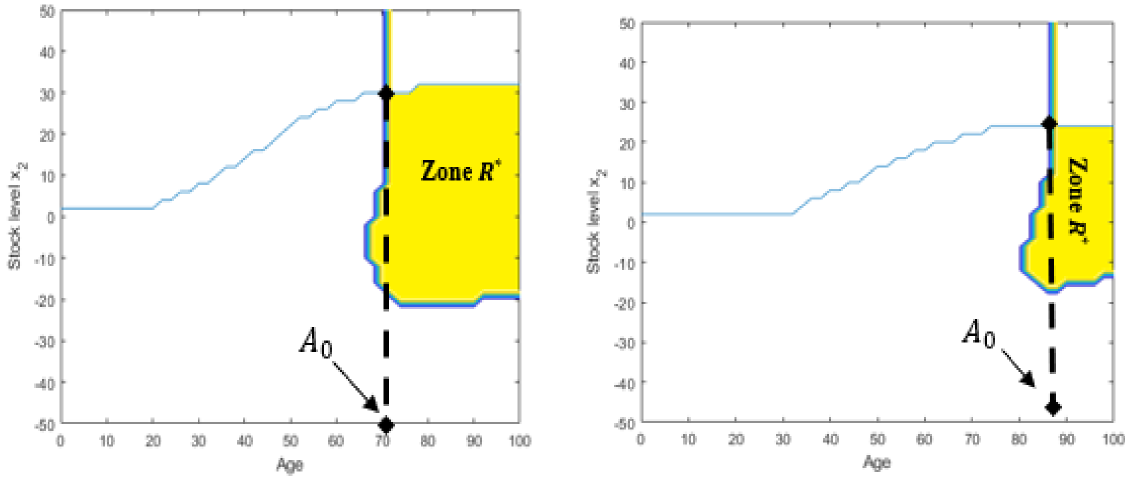


Fig.14. Impact of replacement cost on the production control policy



a) - C_{remp} = 100 b) - C_{remp} = 750

Fig. 15. Impact of replacement cost on the replacement control policy

Comparative study. Most recent research in this field focuses primarily on optimization policies that treat the machine as a production unit subject to random breakdowns and repairs. However, a production policy that considers the operator as a unit facing continuous deterioration due to age has not been previously explored. As we are the first to propose such a strategy, we conducted a comparative study based on the cost function, which reflects the optimal solution in terms of value while accounting for significant age-related deterioration and still meeting customer demand. We employed the numerical approach outlined in Section 2 to determine the optimal policies that minimize costs. We call our strategy Policy-I. As part of the comparative study, we also considered a similar policy found in the literature (Ouaret et al.[29]), which is based only on the controlled replacement rate. The following is a breakdown of our policy and the comparator policy (Policy-II).

- Policy-I: Refers to the optimal policy proposed in this paper. As mentioned earlier, the production and replacement rates are jointly optimized through an integrated model. The system studied in this policy is a function of age-dependent human reliability degradation, where an operator is subject to random shutdowns and rests. In the case of deterioration, the system continues to produce at the rejection rate, with considerable resting time. This policy is furthered distinguished by the fact that the production rate and inventory level are continuously adjustable according to the deterioration level of the production unit.

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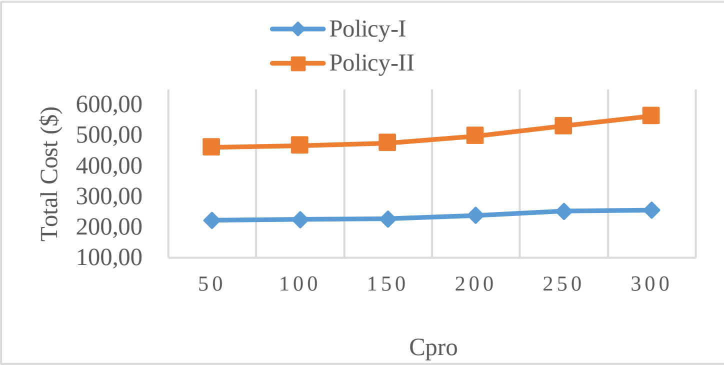
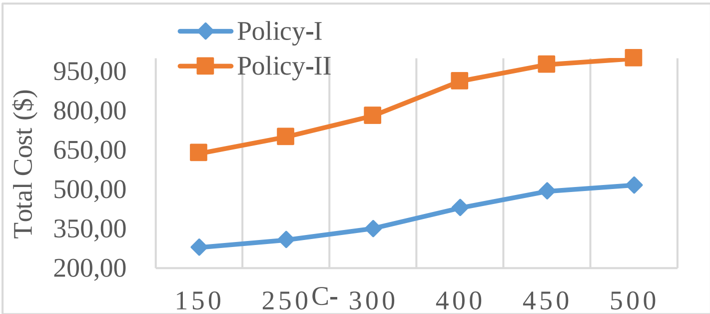
- Policy-II: In this policy, production and replacement decisions are made together, similar to Policy-I. The key distinction in Policy-II is that the production unit will be replaced if deterioration occurs. This policy does not account for random downtimes related to rejection rates and age. Furthermore, the replacement action is based on both the current inventory and the age of the unit.

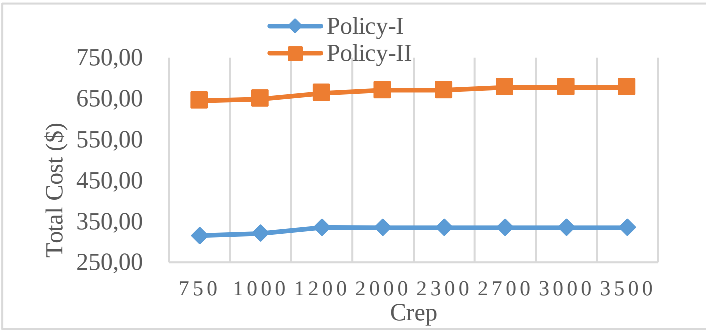
The results displayed in Fig. 16 reveal that for each parameter, the optimal total cost of the proposed policy is always lower than in the second policy. The production unit is therefore replaced more often when the rejection rate increases with age. Also, the production rate is not regular and the stock level is not considered in the decision-making process.



(a) Variation of the production cost



(b) Variation of the backlog cost



(c) Variation of the replacement cost

Fig. 16. Effect of variation of several costs on the total cost for the considered policies

In observing Fig. 16(a), we note that when the production cost increases, it becomes evident that the proposed policy incurs a lower cost than does Policy-II. When the production cost increases, less inventory is allowed, and as a result, the operator produces for shorter time period at a maximum rate; the system deterioration is therefore slower over time, and the replacement drive is delayed. This lower total cost of Policy-I is also due to the fact that it allows for more rest periods, which can be allocated once the system deteriorates. The increased shortage cost, as presented in Fig. 16(b), has significant consequences on the total cost increase. However, the proposed policy remains the cheaper option, mainly because the inventory level is adjusted according to the existing stock level and to the age of the operator in order to avoid costs associated with shortages. As can be seen in Fig. 16(c), when the replacement cost increases, the total cost undergoes a sharp increase because overall, replacement costs are the most expensive. Policy-I always leads to a lower total cost in the comparative study when the replacement cost increases. The system adjusts the rate of production to the rate of demand to prevent the system from deteriorating faster in production.

Perspectives and implementation. The biggest challenge in this study was to define a joint policy that combines human resource management control policies and optimal production control policies under the conditions of the current stock level at time t.

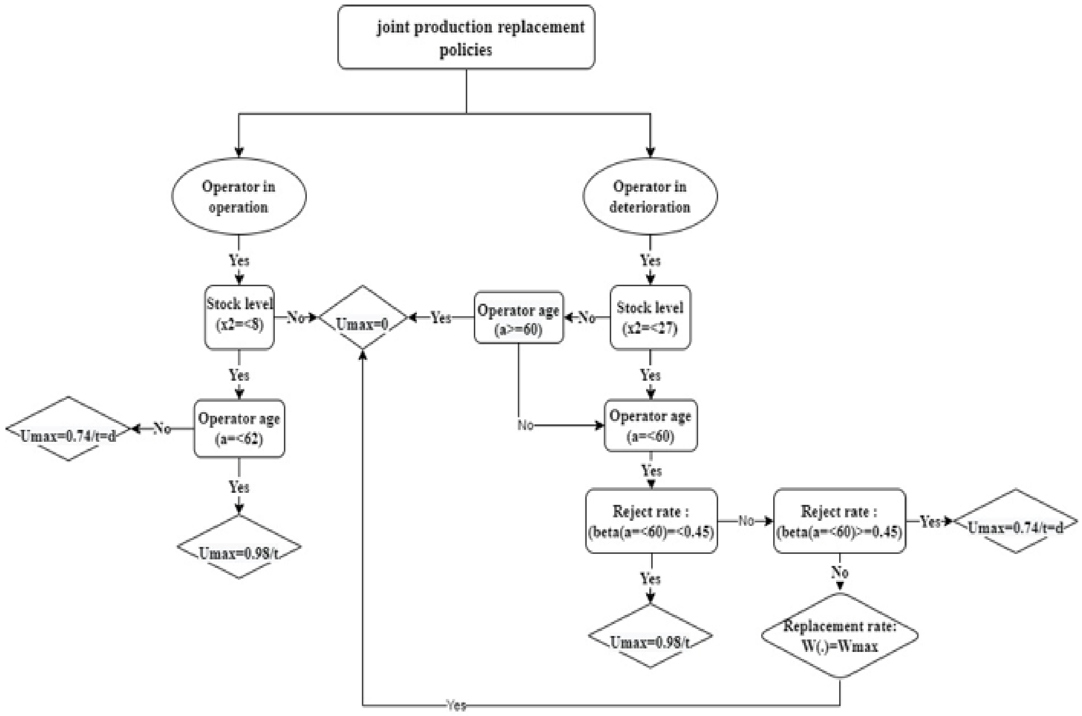


Fig. 17. Perspectives and implementation of the proposed policy

Fig. 17 details the policy proposed in this paper based on the numerical study presented in section 2, using the Kushner numerical analysis approach. It is an implementation of the perspectives and decisions that can be taken when considering the age of the operator, the available stock level, and the number of rejects the operator is producing. Based on the state of the production unit at a given time, the manager first identifies the stock level at the same time. Moreover, there are two possibilities here: operator in operation with a negligible rejection rate or operator in deterioration due to the degradation of its reliability according to age. In the optimal planning situation proposed for the first case, the manager is faced with two possibilities, namely, one where the stock level $x_2(t) \leq 8$ (in this case, the manager will move to identify the age of the producer at time t and will decide to set the production rate at $U_{max} = 0.98/U.T$ if $x_1(t) \leq 62)$ or at the demand rate $U_{max} = 0.74\ /U.T$ otherwise. In the case where $x_2(t) \geq 8$, the decision will be made to set the human production rate to 0. Here, it is recommended to send the operator to rest $R1$. In the case of the second possibility, where the operator is in continuous age-dependent deterioration (state 3), the manager is faced with two possibilities: in the first one, where $x_2(t) \geq 27$, the decision chosen is to stop production only if the operator's age $x_1(t) \geq 60$. At such a high age, it is strongly recommended to replace the operator in order to restore the production system to its initial condition. On the other hand, if the operator's age $x_1(t) \leq 60$, the manager will set the production rate to its maximum when $\beta[x_1(t) \leq 60] \leq 0.45$; if the rejection rate $\beta[x_1(t) \leq 60] \geq 0.45$, the production rate will be set at the demand level and at $U_{max} = 0/U.T$ otherwise. In the latter case, the manager will subsequently decide to replace the operator when considering their high age $x_1(t) \geq 60$, with a rejection rate that exceeds $0.45/U.T$.

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In addition, the manager should know that the production threshold value is affected by the inventory, shortage, and replacement costs. When the inventory cost increases, the production threshold value decreases to avoid overstock, and when the shortage cost increases, the threshold value increases to avoid stockout. For the first scenario, the replacement rate area increases for an age interval value greater than or equal to 62, due to the fact that the production rate of the human system has been set at its maximum for a long time period, which leads to the rapid degradation of human reliability. In the second scenario, the replacement rate area shrinks for a lower value of the age interval greater than or equal to 89, due to the fact that the production rate of the human system was set for a long time below its maximum. For both scenarios, the manager must adjust the threshold value by considering the three parameterized costs, e.g., by often assigning rest cycles with a well-determined duration to a comfortable stock level.

4. Conclusion

This paper examines the challenges of production planning and operator replacement within a dynamic and stochastic framework in a manicuring system. The system comprises a single human production unit that experiences random downtimes and rest periods, producing one type of product over an infinite horizon. We approached the problem using a stochastic control method, treating the operator as a time-degradable manufacturing system with two state variables: stock level and age.

Initially, we defined the structure of the control policy through a numerical method tailored for the optimal stochastic control model. The optimal conditions, framed by the Hamilton-Jacobi-Bellman (HJB) equation, were solved using Kushner's numerical approach to identify the control parameters for the optimal policy. Next, we presented a numerical example to establish production management policies based on the system's age and inventory level. A sensitivity analysis was performed to evaluate the robustness of the proposed joint policy. The findings from this analysis indicated that the results were logical and consistent, further validating the effectiveness of the developed framework.

The comparative study revealed that the proposed policy is more cost-effective than traditional approaches that do not incorporate rest cycles aligned with the deterioration of human reliability. To assist managers in developing an optimal production plan, we have presented a decision-making process in the form of a flowchart. This framework facilitates human resource management decisions based on inventory levels and age. Our approach aims to establish a new production strategy for human-based manufacturing systems, enabling consistent fulfillment of customer demand while maintaining total costs at a manageable level.

Several future research directions have been identified, including: (i) extending the proposed method to encompass systems with multiple machines producing various types of parts, (ii) incorporating product demand uncertainty for seasonal variations, (iii) examining scenarios involving perishable products, and (iv) integrating preventive or predictive maintenance considerations by accounting for system degradation during the production process.

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