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Optimizing JIT production and maintenance strategies for material management in the presence of quality decline and random demand fluctuations

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Abstract: Material management is a critical component of any organization, as it encompasses the efficient and effective handling of materials throughout the entire supply chain process. Just-in-time (JIT) strategies play a vital role in streamlining the supply chain process and minimizing waste. The paper examines the optimization of JIT production management, quality, and maintenance planning in the context of material management. An integrated model is proposed based on optimal control theory to formulate a set of innovative systems dynamics that consider quality decline in a stochastic context. The model also includes random demand fluctuations through a stochastic diffusion process. The objective of the model is to enhance company competitiveness by satisfying a service level constraint and jointly optimizing the JIT production and maintenance control parameters to minimize inventory levels and reduce the total cost. The findings reveal significant interactions between costs and control parameters of both JIT production and maintenance strategies due to their close relationship, leading to the conclusion that the development of an integrative model is more cost-efficient than managing them independently. A comparative analysis further enhances the study by highlighting the potential cost savings in implementing the suggested collaborative control strategy. Overall, the paper contributes to the literature on material management by addressing the research gap in the optimization of JIT production management, quality, and maintenance planning under a stochastic context.

1 Introduction

Delays and extra expenses may be incurred if the materials required for specific activities are unavailable, highlighting the importance of ensuring a timely flow of materials. For effectively managing and controlling materials, it is essential to measure the performance of materials management, devise effective maintenance strategies, cope with quality issues, analyze the effects of deterioration, consider the effect of random demand, etc. In the next paragraphs, we review the literature regarding these common production disturbances.

Maintenance activities have traditionally been viewed in conflict with production activities. To minimize these negative effects, considerable efforts have been made to devise approaches to better align such practices. For example, in [1], an integrated model was developed that examines demand predictions, machine variance, production rates under energy restrictions, and the relationship between production cadences and maintenance techniques. The aim is to determine the ideal lot size while minimizing overall production, energy, and maintenance expenses. [2] developed an integrated production and trading control strategy for unstable manufacturing systems subject to cap-and-trade legislation. The policy directs managers to decide whether to buy or sell permits or increase/decrease production rates to minimize overall costs and reduce carbon emissions. [3] analyzed a proportional risk model and maintenance strategy with many maintenance activities and dynamic control limitations. Condition monitoring is used to detect system degradation, and corrective maintenance activities are established using the system age at failure and deterioration at the start of the production run. [4] compared push and pull disposal inventory controls for a hybrid system with manufacturing and remanufacturing functions and concluded that increasing the disposal rate results in reduced variance values. [5] examined the management of a hybrid production system that handles new or returning materials during the manufacturing process. An intuitionistic model was created to explain financial benefits and make judgments about employing remanufactured components in production processes.

In the sphere of manufacturing, organizations consistently face difficulties in overseeing their activities and procedures related to the management of material, meeting production goals, and maintaining high-quality standards, as in [6], who proposed a paradigm for increasing production quality performance throughout the system ramp-up phases of manufacturing. They studied two strategies, predicting difficulties during design and continually improving the performance metrics. [7] investigated production and maintenance scheduling for an unstable manufacturing system, with an emphasis on just-in-time strategies. This study underlines the value of JIT approaches in reducing the total production cost. [8] provided an effective stochastic analytical model for integrated production and preventive maintenance control in manufacturing systems that experience degradations in reliability and quality. The model optimizes the production and maintenance settings while minimizing the overall cost. [9] presented an effective control strategy that integrates four key choices to coordinate remanufacturing, manufacturing, return replenishment, and quality control while reducing the overall cost and achieving client quality requirements. [10] introduced a model that seeks to develop optimal production plans, preventive maintenance measures, and control chart criteria for quality monitoring. Non-conforming items are available for rework, resulting in lower average costs.

Traditional optimization models for maintenance strategies for sophisticated systems must consider the effects of dependency, such as the degradation of components. Several works address deterioration aspects, such as the article of [11], which focused on production planning for an unreliable, degrading system, with an emphasis on machine deterioration on availability and quality. They determined the production rate and replacement strategy to reduce the total discounted costs. In [12], a hybrid manufacturing system was proposed that divided the production time between manufacturing and remanufacturing. Equipment is prone to degradation owing to the variety of returned items. [13] proposed a model for integrating maintenance plans and spare parts management in a manufacturing system with a constantly growing deterioration rate. This model considers the influence of variations in production rates on system deterioration and demand for replacement components. [14] presented a mathematical model for preventive maintenance that considered inventory, maintenance, and backlog costs. The control policy comprises switching and hedging points, preventive maintenance activation, and production rate management to reduce the surplus of a system with degrading machines. [15] optimized a production system with a machine that deteriorates with time, affecting machine availability and increasing the defective product rate. The objective was to develop a combined policy for production, maintenance, and quality control to increase machine availability, improve product quality, and reduce production costs.

Material management is crucial to ensure a timely flow of materials and avoid unnecessary delays and expenses, which can be achieved through the application of just-in-time strategies that focus on on-time delivery, inventory turnover ratio and reduced lead time, such as the paper of [16], who suggested numerous routing options for just-in-time completion in hybrid flow shops. These solutions employ distributed computing to anticipate the completion durations of unfinished activities in real-time. [17] introduced a novel manufacturing paradigm that attempts to decrease warehouse space while eliminating non-value-adding procedures. They focused on synchronization and uncertainty hedging and employed a manufacturing platform with Internet of things-enabled infrastructure. [18] presented an optimization model for single-machine scheduling that reduces weighted earliness/tardiness penalties and work-in-process expenses for a just-in-time manufacturing system. The model was tested against an existing model and shown to produce optimal solutions for up to six tasks with significantly less computing time than larger models. [19] provided a strategy for optimizing the efficiency of an existing mixed-flow assembly line using an upgraded genetic algorithm and simulation. The technique consists of a multi-objective mathematical model based on the minimal production cycle, part consumption balance, and just-in-time supply of parts. [20] employed a task batching method to divide jobs into batches, an optimum shifting algorithm to determine start timings and a dominance rule for early/late scheduling for just-in-time production scheduling.

The role of logistics operations has grown to become a critical aspect of a firm's competitive strategy. Various elements, including the expansion of global business, limited internal capabilities, and uncertainty can significantly influence businesses. Numerous researchers have examined the impact of demand uncertainty on operations. For instance, [21] addressed a stochastic dynamic distribution issue in which products are shipped from a warehouse to a distribution center with random demand. They provided an optimum selection policy based on inventory thresholds and used a simulation model to illustrate its resilience and performance. [22] investigated the optimal production flow control for a manufacturing company with random demand and uncertainties in price and cost. Their best production strategy is a state-dependent hedging policy that produces only when costs are low and the surplus falls between the two hedging thresholds. [23] proposed a supply chain management model that includes a configurable production rate and price discount for backorders. The model seeks to reduce supply chain costs by optimizing the production rate, lot size, and number of shipments under random demand. [24] the study looks at a capacitated periodic inventory review problem, with an emphasis on the optimal management of raw material and final product stocks, considering random demand and supply. [25] Combined nonperiodic preventive maintenance and production planning optimization for a manufacturing system that includes many machines placed in series with random demand. Experimental findings were provided to investigate the effect of failure rate thresholds on preventative maintenance measures.

As can be seen from the above papers, the connection between production and maintenance strategies is crucial, but further research is necessary in this domain. Existing studies have not fully explored their impact on critical factors such as the presence of uncertainties, product quality, and the use of JIT strategies to minimize costs. Therefore, this study focuses on developing a comprehensive optimization approach for determining the control parameters of a just-in-time production strategy and perfect maintenance policy. The analysis examines the intricate interactions among key strategies, such as production, quality control, and maintenance management, under conditions of high uncertainty. Furthermore, the model considers service-level constraints and random demand modeled through stochastic diffusion processes. Despite the existing models in the literature, none appear to holistically consider all the points addressed in this study.

The remainder of this paper is organized as follows. The second section outlines the suggested control model formulation, while Section 3 introduces the methodology used in this study. Section 4 describes and validates the simulation model developed. Section 5 presents the results and discusses a numerical example along with an extensive sensitivity analysis to highlight the technical benefits of the proposed approach. Finally, Section 6 concludes the study.

2 Formulation of the production model

A Markov process Ω = {1,2,3} defines the system's uptime and downtime. The process is governed by the generator $Q(\cdot) = \{q_{\alpha\alpha'}\}$, where $q_{\alpha\alpha'}$ are the transition rates for states α to α', with $q_{\alpha\alpha'} \geq 0$, and α, $\alpha' \in \Omega$. When the stochastic process $\alpha(t)$ is in state $\alpha(t)$=1, the machine is operational; at $\alpha(t)$=2, the unit is in minor maintenance, leaving the machine in as-bad-as-old conditions (ABAO); and at $\alpha(t)$=3, major maintenance is performed, rejuvenating the unit to its initial settings. The dynamics of stock level x(t) are described as follows (1):

$$\frac{\partial x(t)}{\partial t} = u(t) - \frac{D(t)}{(1-\beta(a))} \tag{1}$$

Where $u(t)$ is the production rate, $D(t)$ is the customer demand, and $\beta(a)$ is the faulty rate. Given such a production model, we hypothesize that demand displays random behavior, as represented by a stochastic diffusion process. We used an Ornstein-Uhlenbeck process with white noise, which defines the following stochastic differential equation (2).

$$dZ_D(t) = -b_1 dZ_D(t) + \sigma_1 W_1(t) \tag{2}$$
$$Z_D(0) = Z_D^0, Z_D^0 > 0$$
$$Z_D^0 \sim N\left(0, \frac{{\sigma_1}^2}{2b_1}\right)$$

Where $Z_D(t)$ is the random component of the demand, b_1 is the coefficient of variation, σ_1 is the diffusion coefficient and $W_1(t)$ represents the Wiener process (3).

$$D(t) = \mu_D + Z_D(t) \tag{3}$$

To simplify matters, we define μ_D as a constant component of the demand. The age of the producing unit $a(t)$ is a function of the operating time, and this age returns to the original value according to the most recent major maintenance conducted, as follows (4), (5):

$$\frac{\partial a(t)}{\partial t} = \eta_0 \cdot u(t) \tag{4}$$
$$a(T) = 0 \tag{5}$$

Parameter η_0 is a constant and T represents the lastest restart of the unit. The quality degradation effect is represented by the following equation (6).

$$\beta(a) = b_0 + b_1\left[1 - e^{-\eta_1 a(t)^{\eta_2}}\right] \tag{6}$$

In the following equation, b_0 represents the defective rate at the initial conditions, b_1 denotes the maximum limit of deterioration, and η_1 and η_2 are nonnegative constants. The system's availability in the operating mode is defined as (7), (8).

$$\Pi_i \cdot Q(\cdot) = 0 \quad \text{and} \quad \textstyle\sum_{i=1}^{3} \Pi_i = 1 \tag{7}$$
$$\Pi_1 = \frac{1}{1 + q_{12}/q_{21} + q_{13}/q_{31}} \tag{8}$$

Furthermore, decision-makers should ensure that the manufacturing unit can satisfy the demand even when it is severely deteriorated. Consequently, the following feasibility requirement must be satisfied (9).

$$u_{max} \cdot \Pi_1 \geq \frac{D(t)}{(1-\beta(a))} \tag{9}$$

The model also included a service-level constraint (10).

$$NS(\cdot) = 1 - \left[\frac{T_{no}}{T_{sim}}\right] \tag{10}$$

Fundamentally, T_{sim} represents the simulation time, whereas T_{no} denotes the period when the client demand is not met. The fundamental hypothesis of the model is to develop a just-in-time (JIT) production policy. The hedging point policy supplements the production of JIT policy as follows (11), (12):

When $a(t) \le B_{JIT}$,

$$u^*(1,x,a) = \begin{cases} u_{max} & if \quad x(t) < 0 \\ D/(1-\beta(a)) & if \quad x(t) = 0 \\ 0 & if \quad x(t) > 0 \end{cases} \qquad (11)$$

When $a(t) > B_{JIT}$,

$$u^*(1,x,a) = \begin{cases} u_{max} & if \quad x(t) < Z_p \\ D/(1-\beta(a)) & if \quad x(t) = Z_p \\ 0 & if \quad x(t) > Z_p \end{cases} \qquad (12)$$

In Equation 12, as the system deteriorates and reaches age B_{JIT}, some inventory Z_p is maintained as a safeguard against defects and breakdowns. According to the specification of the maintenance policy, major maintenance occurs when age $a(t)$ exceeds trigger point A_0. Therefore, the plan for major maintenance implies that (13).

$$\omega^*(1,x,a) = \begin{cases} 1 & if\ a(t) \ge A_0 \\ 0 & otherwise \end{cases} \qquad (13)$$

In practice, A_0 is the age that which major repair is initiated. The optimization parameters are also important considerations for the model. The inventory-backlog cost IB(t) in period [0,T] was determined using the following equation (14):

$$IB(t) = \frac{1}{T}\int_0^T \left(C^+x^+(t) + C^-x^-(t)\right)dt \qquad (14)$$

with

$$x^+ = max(0,x)$$
$$x^- = max(-x,0)$$

Constants C^+ and C^- punish inventory costs and shortages, respectively. The average overall quality cost $QC(t)$ is calculated using the average cost of defects C_{def} per unit of time as follows (15):

$$QC(t) = \frac{1}{T}\left(C_{def}\int_0^T (\beta(t)\cdot d)dt\right) \qquad (15)$$

The average MC(t) for the maintenance cost includes both the cost of minor maintenance and the cost of major repairs (16).

$$MC(t) = \frac{1}{T}\cdot\left(C_R \cdot N_R(t) + C_M \cdot N_M(t)\right) \qquad (16)$$

In the current problem, $N_R(t)$ and $N_M(t)$ represent the number of minimal repairs and major maintenance performed throughout the period [0,T]. Minimization implies the following stochastic model (17):

$$Min\ TC(Z_p, B_{JIT}, A_0) = \lim_{t\to\infty}\left(IB(t) + QC(t) + MC(t)\right) \qquad (17)$$

Subject to:
$NS(\%) \le NS_L$
Equations (1)-(9) (Inventory and quality dynamics)
Equations (11)-(13) (Control policy)
$Z_p, B_{JIT}, A_0 \ge 0$

The practical implication of NS_L is that it indicates the service level required by customers.

3 Methodology

Owing to its flexibility and capacity to reproduce stochastic dynamics, a simulation-optimization technique has proven to be effective in establishing the best control settings when dealing with such uncertainties. This section outlines the selected method. We specifically used simulation and optimization approaches to properly model the dynamic behavior of the production unit. We created an analytical model and then used the high flexibility of the simulation approaches to find a solution. Statistical studies, including experimental design and response surface approaches, have also been utilized to optimize the model parameters. This method has been successfully utilized in earlier research on systems with challenging analytical solutions [7]. The suggested control model was solved using the technique described below, taking these actions into account.

I. **Mathematical formulation:** in this phase, the mathematical formulation of the manufacturing unit under analysis is carried out through a series of equations that define the dynamics for inventory and machine age; it is also determined the stochastic differential equation used to model random demand, as well as the equations used to define production and repair control policy. Equations (1)-(17) are used to model the industrial system analytically.

II. **Simulation model:** in this stage, a simulation model is created that includes both discrete and continuous components, with the goal of capturing the dynamics of the production system. The control parameters (Z_p, B_{JIT}, A_o) specified in the preceding phase defined the input of the simulation model. Additionally, the simulation model was validated during this phase.

III. **Statistical analysis:** this phase entails conducting an ANOVA study to determine the relevant control factors and their interactions that must be addressed in the minimization. Consequently, simulation results are required to perform such an analysis, which leads to the definition of a second-order regression model for total cost. Statistical analysis was performed using an experimental design with three replicates.

IV. **Optimization:** in this stage, we specify the experimental domain for the control parameters

(Z_p, B_{JIT}, A_o). The goal is to apply the response surface approach to optimize these parameters while lowering total costs. Consequently, the regression model employed in the previous phase was optimized, which required several simulation runs. The response surface determines the optimal control factors $(Z_p^*, B_{JIT}^*, A_o^*)$ and optimal cost.

V. **Sensitivity analysis:** in this stage, a variety of actions are performed to validate the chosen approach and ensure that accurate results are produced. The initial task is to track various important simulation model performance indicators to ensure that the simulation model accurately captures the dynamics and stochastic behavior of the manufacturing unit. Furthermore, the variability of many costs and system factors was examined to analyze the robustness of the proposed control strategy. This section is supplemented by a comparative analysis that focuses on the economic cost reductions provided for our approach.

4 Simulation model

The idea behind the procedure involves creating a combined discrete-continuous simulation model (Figure 1) to replicate the dynamics and flow of the proposed production system. The Arena simulation software is used to develop the model, which uses control parameters and the Runge-Kutta-Fehlberg algorithm to update differential equations for the stock level and machine age. The model estimates the random duration of failures and maintenance actions, and a C++ subroutine defines the continuous part of the model that simulates the trajectory of the stochastic differential equation of random demand. The discrete and continuous sections were synchronized to imitate uncertain manufacturing system features. Production and maintenance strategies are implemented based on the control rules denoted in Equations (11)-(13), and several modules detect the machine's stock level and age to trigger major maintenance and adjust the production rates. After the simulation run, the indicators define the average stock level, backlog, defective cost, and repair cost using Equations (14)-(16). Simulation-optimization approaches are an efficient alternative for providing adequate solutions within a reasonable time.

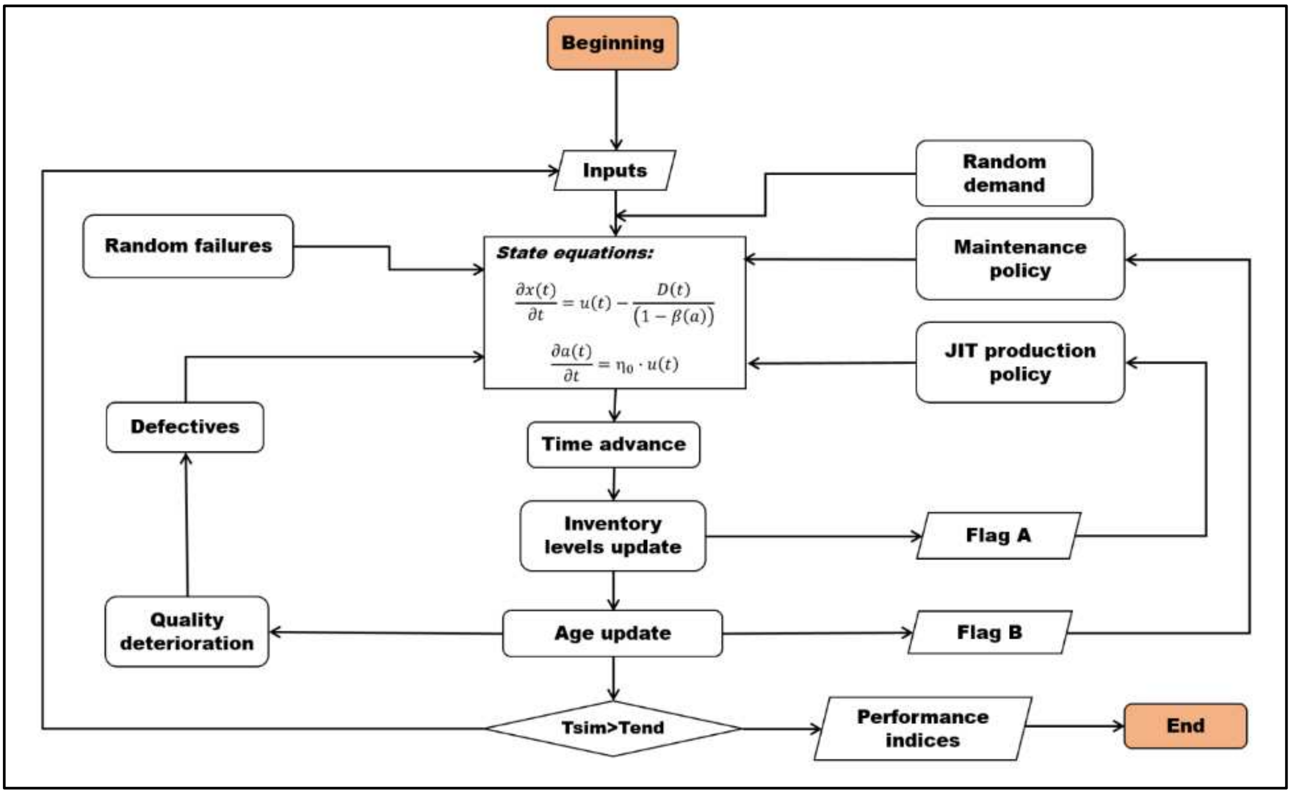

Figure 1 Simulation model

4.1 Evaluation of the simulation model

The simulation model was evaluated to ensure accuracy of the results. The key metrics of the system's performance are monitored, and Figure 2 shows the dynamics of the production system when the control parameters are set to Z_p=20, B_{JIT}=150 and A_o=250. The system is in AGAN conditions when $t = 0$ (see circle 2 in Figure 2) and then experiences malfunctions and failures at $t = 90$ (see circle 2). Then, at $t = 150$, the system reaches $B_{JIT} = 150$ and inventory increases from zero to $Z_p = 20$ (see circles 4 and 5). Changes in inventory thresholds indicate that cumulative degradation leads to increased defects, requiring more inventory to satisfy the demand using defect-free units. At $t = 240$, the system produces at a rate

$d/(1-\beta\,(a))$ (see circle 6), which is given to mitigate the generation of non-conforming units originating from the deterioration process (see circle 7). When the system surpasses age $A_o = 280$, it performs a major repair (see circle 8), thereby reducing inventory. The rate of defects significantly decreased after the major repair, as it rejuvenated the system and removed the defects. The inventory level was set back to zero, indicating the start of a novel degradation cycle (see circles 9-11). The assessment of the dynamics in Figure 2 demonstrates that JIT production and the major repair strategies function correctly. Once the system surpasses the reference age B_{JIT}, some inventory is required to mitigate shortages; if the system ages above A_o, major maintenance is conducted.

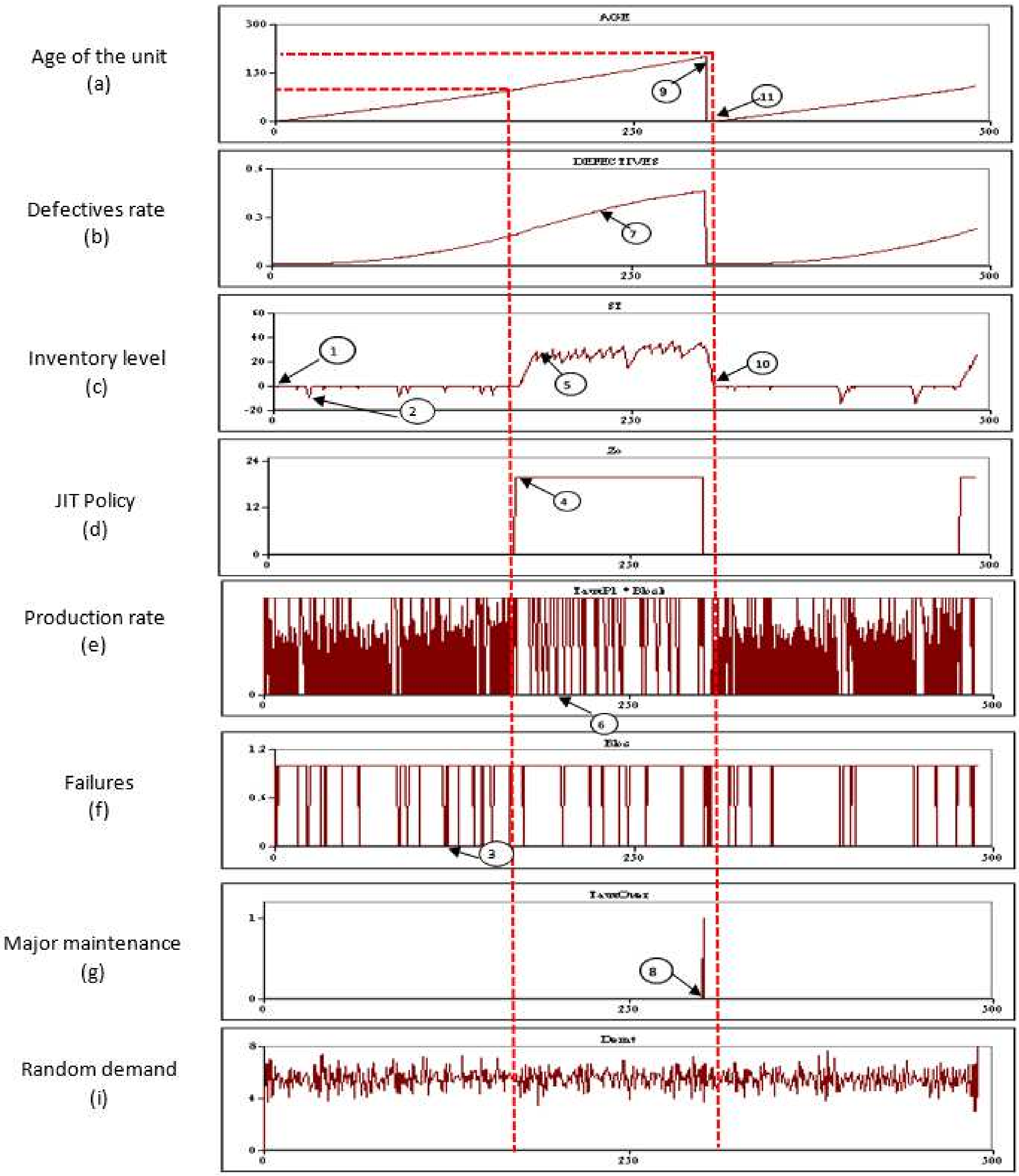

Figure 2 Graphical validation of the simulation model

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5 Result and discussion

For illustrative purposes, 108 simulation runs were performed using a design of experiments replicated four times: $(3^3x4) = 108$. The simulation was set to 100,000 time units to ensure steady-state conditions. The parameters of the numerical example are listed in Table 1.

Table 1 Data for the simulation model

Parameter:	q_{12}	q_{21}	q_{13}	q_{31}	θ	
Value	0.1	1.5	5	0.15	0.08	
Parameter:	u_{max}	d	η_0	b_0	b_1	C_M
Value	9	5.5	0.1	0.01	0.49	3000
Parameter:	η_1	η_2	C^+	C^-	C_R	C_{def}
Value	15x10^ -6.2	2.4	1	50	100	20

Table 2 shows the levels of the independent variables (Z_p, B_{JIT}, A_o) utilized in the simulation instance, which were determined by offline executions. To ensure that $B_{JIT} < A_o$, we define $B_{JIT} = k \cdot A_o$, where k ranges from 0 to 1.

Table 2 Control parameters

Factor	Lower level	Higher level	Description
Z_p	10	150	Optimal inventory level
k	0.1	0.9	Auxiliary variable
A_o	40	300	Reference age for major maintenance

The simulation model produced sufficient data to construct a second-order regression model for total cost.

$TC(Z_p, k, A_o)$ = 540.589 - 3.80285*Zp - 353.417*k - 2.20742*Ao + 0.0117889*Zp^2 + 1.18843*Zp*k + 0.00374364*Zp*Ao + 477.796*k^2 - 0.225722*k*Ao + 0.00522249*Ao^2 (18)

Table 3 shows the ANOVA results for the aforementioned equation, indicating a correlation value of R^2= 0.902. This statistic indicates that the regression model explains 90.20 percent of the observed variability in total cost.

Table 3 ANOVA results

Source	Sum of Squares	Gl	Medium Square	F-Ratio	P-Value
A:Zp	83008.7	1	83008.7	22.01	0.0000
B:k	188873.	1	188873.	50.09	0.0000
C:Ao	36562.0	1	36562.0	9.70	0.0033
AA	40042.7	1	40042.7	10.62	0.0022
AB	26575.2	1	26575.2	7.05	0.0111
AC	27853.6	1	27853.6	7.39	0.0094
BB	70130.5	1	70130.5	18.60	0.0001
BC	3306.48	1	3306.48	0.88	0.3543
CC	93478.0	1	93478.0	24.79	0.0000
blocks	562.859	1	562.859	0.15	0.7011
Total error	162139.	43	3770.68		
Total (corr.)	732532.	53			

Table 3 presents the P-values of the main factors and interactions included in the ANOVA, where we identify in red the significant factors that must be included in the optimization phase. A P-value lower than 0.05 indicates strong evidence that such factor has a significant impact on the total cost. Figure 4 presents the regression model projection for the total cost in two-dimensional space. Figure 4 shows the optimal solution, which is presented in Table 4. The variable k^* = 0.2609 leads to B^*_{JIT} = 45.35. The optimal parameters presented in Table 4 are the proposed values for concurrently regulating production pace and major maintenance performance.

Table 4 Optimal value of the control parameters

	Zp*	k*	Ao*	Estimated Total Cost
Control factor	120.539	0.261	173.771	73.47

5.1 Sensitivity analysis

In the sequel, we evaluate the sensitivity of various costs. Table 5 presents the results of the sensitivity analysis of the most typical costs.

- Variability of the shortage costs: as the shortage cost increases (case 4), the lack of product is punished more harshly. As a countermeasure against shortages, inventory levels increase, resulting in an increment in Z_p as a safety reserve. Furthermore, we discovered that product shortages resulted in a drop in the critical age B_{JIT}, implying that the unit applies the JIT approach for a shorter amount of time, allowing inventory to be maintained for longer. The increase in the shortage cost puts huge pressure on the system's performance; thus, major repairs are postponed to guarantee that the machine remains in operation for a longer duration and to prevent shortages.

Table 5 Variability of the cost parameters (↑ and ↓ indicate the impact of varying the cost element)

Par.	Value	Case	Z_p	k	B_{JIT}	A_o	Total cost ($)	Effect
		Base case	*120.53*	*0.261*	*45.35*	*173.77*	*73.47*	-
C+	0.5	case 1	139.48	0.118	20.72	175.50	28.18	Zp↑,Bjit↓,Ao↑
	2	case 2	97.13	0.417	72.82	174.71	127.54	Zp↓,Bjit↑,Ao↑
C-	20	case 3	88.37	0.463	82.55	178.36	80.55	Zp↓,Bjit↑,Ao↑
	70	case 4	130.33	0.188	32.69	174.06	55.26	Zp↑,Bjit↓,Ao↑
C_R	20	case 5	120.51	0.261	45.43	173.98	66.16	Zp↓,Bjit↑,Ao↑
	500	case 6	120.69	0.260	44.91	172.70	110.03	Zp↑,Bjit↓,Ao↓
C_M	1000	case 7	122.30	0.256	42.03	163.95	65.98	Zp↑,Bjit↓,Ao↓
	5000	case 8	119.12	0.265	48.08	181.69	80.21	Zp↓,Bjit↑,Ao↑
C_{def}	5	case 9	118.76	0.265	48.31	182.15	60.25	Zp↓,Bjit↑,Ao↑
	50	case 10	124.11	0.252	39.53	156.56	97.82	Zp↑,Bjit↓,Ao↑

- Variability of the cost of major repair: The increase in the expense of major repairs CM (case 8) causes delays in maintenance and increases the age of A_o. This result is explained by the fact that the system must attain greater degrees of deterioration to compensate for the high expense of major repairs. Furthermore, the goal of performing fewer major repairs is to allow the system to run for longer periods of time without interruption, resulting in an increased production capacity and a lower priority for stock maintenance. Thus, this operation lowers stock level Z_p. Furthermore, when the production time increases, the JIT approach is extended, which increase the age of B_{JIT}. The reduction in the major repair cost had the opposite impact (case 7).
- Variability in cost of defectives: With the increase in the cost of faulty components, C_{def} (case 10), it is observed that major maintenance is carried out more frequently to rejuvenate the system faster and limits the number of non-conforming units found by the end user. Furthermore, a careful study of the rise in the cost C_{def} demonstrates that the system has opted to increase the inventory level to ensure that consumers are satisfied with faultless units. This strategy was supplemented by lowering the critical age of B_{JIT}, allowing for a longer time for inventory policy implementation. When the cost of faulty items is reduced (Case 9), the opposite consequences occur.

An argument can be made to assert that the structure of the control strategy in Table 5 is robust and consistent throughout the analysis.

5.2 Sensitivity of the Ornstein-Uhlenbeck process

Our primary concern in the present subsection is the analysis of the variability of the stochastic differential equation parameters σ_1 and b_1, which describe the dynamics of random demand. Table 6 presents the results of the sensitivity analysis.

Table 6 Sensitivity for the Ornstein-Uhlenbeck process parameters

Case	σ_1	b_1	Z_p^*	k^*	B_{JIT}^*	A_o^*	Cost*	Service level
Base case	*0.6*	*1.5*	*120.539*	*0.261*	*45.351*	*173.771*	*73.474*	*0.910*
Sensitivity for σ_1								
case 11	0.15	1.5	120.052	0.266	46.484	174.607	74.772	0.907
case 12	0.7	1.5	121.032	0.259	44.906	173.285	73.614	0.912
case 13	1.25	1.5	122.044	0.252	43.206	171.566	71.460	0.920
Sensitivity for b_1								
case 14	0.6	0.25	126.928	0.168	27.531	163.879	51.103	0.942
case 15	0.6	1	121.037	0.256	44.346	173.343	73.049	0.911
case 16	0.6	1.75	120.146	0.262	45.483	173.746	73.612	0.913

- Variation of parameter σ_1: As parameter σ_1 increases (case 13), major repairs are performed more frequently to reduce the production of defective units. Additionally, increasing σ_1 indicates that the production unit tends to increase inventory level Z_p to ensure that demand is met with defect-free products. This step is paired with lowering the reference age B_{JIT} to extend the amount of time during which the inventory strategy maintains more stock to guard against demand fluctuations. This action allows for the availability of a greater stock to replace faulty units as needed. Increasing the parameter σ_1 results in an increase in inventory owing to increased demand fluctuation and the requirement for greater protection. When parameter σ_1 declines, there are inverse impacts (see case 11).
- Variation of parameter b_1: By increasing parameter b_1 (case 16), it is observed that major maintenance is performed less frequently because there is less variation in the fluctuation of demand in the short term, which increases age A_o. Additionally, the just-in-time policy is used more frequently, which increases the age B_{JIT}, because demand varies less in the short term, and less inventory is required for protection. As a result, the stock level Z_p decreases. When parameter b_1 is reduced (case 14), the converse occurs.

5.3 Service level constraint sensitivity

In the following subsection, Table 7 examines the impact of service-level constraints. The resulting service-level regression equation is as follows.

$$\mathrm{NS}(Z_p,k,A_o) = 0.747988 + 0.00223376{*}Zp - 077464{*}k + 0.00121354{*}Ao - 0.00000650{*}Zp\text{^}2 - 0.00109992{*}Zp{*}k - 0.00000094{*}Zp{*}Ao - 0.175613{*}k\text{^}2 - 0.00044982{*}k{*}Ao - 0.00000281{*}Ao\text{^}2 \quad (19)$$

Further investigation shows that varying the service-level parameter NS_L leads to the following implications.

- Variation of the service level constraint: As the service level parameter NS_L, drops (case 22), major maintenance is conducted less often, increasing A_o. This is because of the need to keep the system operating for a longer duration to prevent product shortages. As the service level decreases, the inventory level Z_p is expected to decrease, as the requirement for greater safety stock decreases. Furthermore, when the service level is lowered, the just-in-time strategy is postponed, because maintaining inventory at low service levels is unnecessary. When the service level increased, the outcomes were inverse (case 17).

Table 7 Sensitivity of the service restriction

Case	Service level NS_L (%)	Z_p^*	k^*	B_{JIT}^*	A_o^*	Cost*
case 17	94%	120.270	0.264	45.988	173.943	73.480
case 18	92%	116.422	0.314	55.456	176.768	74.709
case 19	90%	112.740	0.361	65.063	180.158	77.938
case 20	88%	109.219	0.407	74.863	184.081	82.947
case 21	86%	105.836	0.450	84.892	188.488	89.545
case 22	84%	102.620	0.492	95.183	193.351	97.563

5.4 Comparative study

For the sake of completeness, we evaluate the performance of the suggested policy (Z_p,B_{JIT}, A_o), also known as Policy-A, to other policies found in the literature.

- Policy-B: This option does not implement the JIT policy. In this case, the production strategy focuses only on establishing the appropriate Z_p inventory level, which remains constant across the time period under consideration. This option does not include control factor B_{JIT} in the optimization. Thus, Policy-B includes only the parameters (Z_p,A_o) in the control policy, which are jointly optimized. This policy assumes random demand.

- Policy-C: The control policy does not apply the major maintenance strategy; instead, inventory level and age are used to implement the just-in-time policy. Therefore the control parameters are just (Z_p,B_{JIT}). This policy assumes a random demand.
- Policy-D: In this policy, a constant demand is considered, and the just-in-time policy is not applied, therefore there are only two control parameters (Z_p,A_o), one devoted to the optimal value of the stock level and another parameter to indicate the age at which the major repair is performed.
- Policy-E: This policy uses constant demand and just two control parameters, one for stock level and one for age, to execute the just-in-time policy (Z_p,B_{JIT}). Parameter A_o for major maintenance is discarded.

Table 8 shows the findings of the comparison analysis.

Table 8 Comparative study

Descripción	Z_p^*	k^*	B_{JIT}^*	A_o^*	Cost*	Cost difference
Policy-A	120.27	0.2643	45.98	173.94	73.47	-
Policy-B	104.07	-	-	159.75	113.82	54.92%
Policy-C	90.99	0.5006	100.13	200	128.03	74.25%
Policy-D	103.71	-	-	161.18	112.13	52.62%
Policy-E	90.759	0.5062	101.25	200	128.00	74.22%

Regarding Policy-C, had the greatest cost of the comparison because it separates maintenance decisions from the optimization; this policy exclusively optimizes the production parameters (Z_p,B_{JIT}). Policy-III reduces inventory levels and extends the zero-inventory policy. However, postponing major maintenance has significantly increased the total costs by generating more defects. The cost increase of Policy-E is observed as a result of separating the optimization, manufacturing, and repair control factors. Table 8 validates the key economic benefits of Policy-A, as it clearly indicates that Policy-A always had the lowest cost compared to other choices.

6 Conclusions

This study explores the optimization of just-in-time (JIT) production, maintenance strategies, and quality control for material management in organizations. The main objective of this study is to fill the research gap by investigating the impact of JIT strategies on the efficiency and effectiveness of organizations. Four key factors motivated this research: the consideration of the interaction of the strategic functions of production-quality-maintenance, the determination of optimal factors of production and repair strategies based on system degradation levels, the implementation of a zero inventory just-in-time strategy before the system reaches a certain age, and the need for repair policies based on product quality data that consider the relationship between system deterioration and non-conforming units. To achieve this objective, an integrated model based on optimal control theory was developed to formulate a set of innovative system dynamics that considers quality decline in a stochastic context with random demand fluctuations. The findings of the research revealed significant interactions between the costs and control parameters of both JIT production and maintenance strategies, leading to the conclusion that an integrative model is more cost-efficient than managing them independently. However, the limitation of the study is the assumption that quality deterioration follows a certain known pattern, whereas in practice, the generation of defectives exhibits random behavior. Therefore, in future studies, random generation of defectives will be explored.

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