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A Novel Approach for Planning Imperfect Preventive Maintenance in Manufacturing Systems by a Simulation-Optimization Approach

Taha-hossein Hejazi[a]*, Bahareh Hekmatnia[b], Mehrad Soltanzadeh[c]

[a] *Department of Industrial Engineering, Amirkabir University of Technology, Garmsar Campus, Iran.*
[b] *Department of Industrial Engineering and Management, Sadjad University of Technology, Mashhad, Iran.*
[c] *Department of Management, Kheradgarayan Motahhar Institute of Higher Education, Mashad, Iran.*

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ABSTRACT

This study addresses simulating manufacturing processes and maintenance activities in a multi-product industry to model the complexity of interactions between maintenance strategies and their effects on a manufacturing system. A novel simulation model has been developed using Discrete Event Simulation (DES) to investigate interactions between manufacturing and maintenance systems. A real two-product manufacturing line in an automotive factory was studied to demonstrate the proposed model's efficacy. Two significant challenges were considering Preventative Maintenance (PM) as imperfect PM activities and estimating unknown probability distribution in a real industry. These are new assumptions that generally have not been considered in the prior studies. To overcome these problems, imperfect maintenance activities are defined as different scenarios and unknown probability distributions are estimated based on historical records in the case study. A simulation-based optimization method was developed using OptQuest, and the results of the proposed method were then compared with the current values in the case study. The findings illustrate that the proposed model can reduce the system's manufacturing and maintenance costs by 13%. In addition, the implementation of maintenance planning in this research improved some factors in the manufacturing system efficiently.

Keywords

Preventive maintenance, Simulation-Optimization, Imperfect maintenance, Maintenance cost, OptQuest.

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****Corresponding author***
Email: t.h.hejazi@aut.ac.ir

1. Introduction

Research on maintenance planning was established decades ago, and different approaches are applied to investigate efficient maintenance operations. Some studies are reviewed in the literature in two separate parts, including mathematical and simulation models. The majority of mathematical models have discussed costs and reliability. De Almeida (2012) proposed a multi-criteria decision making (MCDM) approach to select the best preventive maintenance intervals that reduce total cost. Wang and Zhang (2013) surveyed the replacement problem, which consists of two types of failures. The first one is repairable in which maintenance activities are carried out by technicians to repair the system and the second one is unrepairable that the whole system needs replacing at once. The process aims to find the optimal replacement policy, which leads to the minimum average cost rates. Chen et al. (2015) focused on a prognostic model that determines physical deterioration in a stochastic process to minimize the total operational costs, including preventive/corrective, replacement, and downtime costs. Imperfect maintenance is another principal issue related to the optimization of complex maintenance systems. Lim et al. (2016) proposed a repair model, which could find the optimal replacement age in a system with an imperfect repair policy. Aghezzaf et al. (2016) also developed a Mixed Integer Nonlinear Programming (MINP) to represent a manufacturing system where production and maintenance decisions are assumed integrated and preventive maintenance activities occur imperfectly. A heuristic procedure was applied to solve this complex problem. Concerning safety in an industrial environment, Martón et al. (2016) developed Multiple Objective Optimization Problems (MOP) to obtain the optimal maintenance intervals in a maintenance system. The application case that contains multiple items appears that efficient test intervals and maintenance activities had a significant impact on detecting hidden failures. Jun et al. (2017) proposed a mathematical model to estimate the long-run cost Condition-Based Maintenance (CBM) system. To illustrate the maintenance policy, a case study is employed, and the degradation process is described with known and unknown distribution parameters. It is realized that the distribution of the system's lifetime was deeply affected by the degradation rate. Driessen et al. (2017) considered three deterioration states, including normal, defective, and failed states to minimize the average cost over an infinite time horizon by optimizing the maintenance policy. The numerical study demonstrates that the model with constant probabilities costs, on average, 19% higher than non-constant probabilities of inspection errors. Liu et al. (2018) created an integrated decision model that coordinates degradation information of maintenance activities, taking into account the health status and machines' age. A single-machine system is used as a case study to demonstrate the value of the proposed method. Nguyen et al. (2019) defined a new objective of grouping individual PM strategies to maximize the planning horizon's profit. On the other hand, some studies do not restrict the maintenance grouping into finite planning and propose a model without specifying the horizon (Wu et al., 2020). Furthermore, some researchers applied predictive group maintenance for multi-system multi-components networks (Liang and Parlikad, 2020) and then, forecast demand distribution for spare parts based on the maintenance plan (Zhu et al., 2020). All these studies entailed mathematical models to optimize maintenance intervals and replacement strategies. It is observed from the literature that most studies considered cost and reliability functions as objectives.

One of the most common approaches in simulating the maintenance system is Monte Carlo simulation. Besnard and Bertling (2010) applied Monte Carlo simulation to compare three maintenance strategies: visual inspection, inspection with a condition-monitoring technique, and online condition monitoring. The results showed that for systems with high rate failure, online condition monitoring is the optimal strategy. Liu et al. (2016) developed a maintenance model that considers long-run cost rates as objective and aims to find the optimal threshold for imperfect PM action. Some previous studies extended the simulation-optimization approach to integrating maintenance and manufacturing systems. Roux et al. (2013) combined several tools to ensure a low frequency of failures and efficient preventative maintenance thresholds. Furthermore, the impact of PM strategy on the production line was studied in this proposed model. Alrabghi and Tiwari (2016) proposed a simulation approach to minimizing the total cost consists of the maintenance cost, spare parts cost, and unavailability cost. To optimize the problem, Simulated Annealing (SA) was used, and the results were compared with other optimization algorithms. Lam and Banjevic (2015) used a proportional hazards model for risk of failure and a Markovian process to model the system covariates. This approach is studied to determine the optimal maintenance inspection in a CBM model. Many studies on maintenance systems used simulation as a vital tool to find the best maintenance decision in complex and multi-component systems (Coit et al., 2015, Sharifi and Taghipour, 2023, Bisht and Singh, 2023). Babishin and Taghipour (2016) studied a multi-component system to obtain the optimal maintenance policy. Their research considers hard and hidden failures for all components and periodic inspection interval is found for the system. Hajipour and Taghipour (2016) developed a simulation model to obtain optimal non-periodic inspection intervals in different multi-component systems. A Genetic Algorithm (GA) was applied to find the minimum total expected cost over the system's lifecycle. Nyemba and Mbohwa (2017) simulated both material flow and maintenance in a multi-product manufacturing system by Arena Simulation Software. Alrabghi et al. (2017) applied a stochastic Discrete Event Simulation (DES) approach to finding the optimal maintenance strategy in two industrial systems. These strategies include Corrective Maintenance (CM), PM, Opportunistic Maintenance (OM), and CBM. The findings suggest a new approach to considering production dynamics in maintenance planning. Regarding spare parts planning, Sharma et al. (2017) proposed a simulation-optimization approach that could forecast future failures while keeping the cost to a minimum. Using GA and simulation, the model aimed to determine the number of spare parts for army equipment with selective maintenance strategies. Wakiru et al. (2019) also defined a simulation approach that study some effective factors such as repair time and availability in a thermal power plant. Finally, different maintenance strategies, the time between overhaul and spare parts have been introduced as the most effective factors for reducing the repair time. Also, the impact of the maintenance policy on the inventory system was investigated in a simulated numerical study (Poppe et al., 2017b). It is understood from the literature that the majority of studies apply a simulation approach to optimize maintenance planning and decrease maintenance costs. Studies that employed simulation in maintenance are highlighted in Table 1. Finally, the new decision variables and approaches in the current research are mentioned and compared with previous studies.

To summarize, maintenance activities typically take the time that could be allocated for manufacturing; however, delaying maintenance may increase the probability of machine failure. Consequently, trade-offs and conflicts between maintenance planning and manufacturing systems should be considered in real industrial environments (Liu et al., 2018). Maintenance in manufacturing systems with an integrated assembly line is particularly crucial because if a workstation or machine fails in this kind of system, the full line may stop working. Thus, maintenance activities are essential to keep the manufacturing system or to restore it to an acceptable productivity level (Aghezzaf et al., 2016).

This paper aims to develop a model to generate optimal imperfect PM periods by considering the relevant manufacturing data in a real industrial case. Based on previous maintenance research, simulation models, which are typically appropriate models to consider both manufacturing and maintenance systems in detail, is used in this paper. The key questions are "How to illustrate a methodology to model the maintenance system in this two-product manufacturing line" and "What is the effect of considering imperfect PM activities in a real industrial environment. To overcome these challenges, this paper proposes a new approach to model maintenance activities in the factory. Imperfect PM maintenance activities are defined as three scenarios in which total costs are evaluated. Then the best scenario is selected to fulfill in the case study. Another new assumption is that some data such as repair time and Mean Time Between Failures (MFTB) were unknown in the case study, so they needed to be estimated based on recorded data. Overall, this model enables the decision-makers to decide about PM intervals while the manufacturing system is operating and costs are evaluated in the whole system. Simulation-based optimization is applied to obtain the optimal decision variables. The proposed model could successfully decrease the costs and improve some factors in the manufacturing system.

The remainder of the paper is organized as follows. Section 2 discusses the methodology and explains the assumptions in the model. Section 3 introduces the proposed simulation model in detail. Section 4 indicates the case study and the results. Section 5 discusses the results, and finally, Section 6 summarizes the conclusions.

Table 1. Summary of simulation-based approaches for maintenance strategies

Research	Objective function	Decision variables	Solution Method	Case study
Liu et al., (2018)	Production cost and tardiness cost	Job sequence PM intervals	GA	A research laboratory facility
Besnard and Bertling, (2010)	Costs of maintenance strategy	Maintenance inspection time	Monte Carlo simulation	Wind turbine
Liu et al., (2016)	Long-run cost rate	The threshold for imperfect PM action	Monte Carlo simulation	-
Roux et al., (2013)	Unavailability of the system	PM inspection interval	Nelder–Mead (Simplex) method	-
Alrabghi and Tiwari (2016)	Total cost (maintenance cost, spare parts cost, and unavailability cost)	Preventive maintenance frequency, and the type of maintenance strategy	Simulated Annealing (SA)	-
Lam and Banjevic (2015)	Costs of maintenance policy per unit time	Next PM inspection time	Simulate possible scenarios by Markovian process	-
Babishin and Taghipour (2016)	The total cost of maintenance and repair policy	Periodic inspection interval	Simulation Of each maintenance policy	-
Hajipour and Taghipour (2016)	The total expected cost of the system over the lifecycle	non-periodic inspection scheme	Simulation and GA	-
Nyemba and Mbohwa (2017)	Production costs	Production and maintenance intervals	Simulation via software	Furniture assembling plant
Alrabghi et al., (2017)	Maintenance cost and the production throughput	Maintenance strategy	Non-dominated Sorting Genetic Algorithms (NSGA II)	A tyre re-treading factory and a petrochemical plant
Sharma et al., (2017)	Maintenance cost	Maintenance replacements	GA	Army equipment

Research	Objective function	Decision variables	Solution Method	Case study
Wakiru et al., (2019)	Total repair time	The time between overhaul, Fill rate that deals with the inventory policy, Maintenance strategy reliance factors	Design of Experiment (DOE)	Thermal power plant
Poppe et al., (2017a)	Inventory costs of maintenance policy, Maintenance intervention costs of maintenance policy	Reorder point, Order quantity, Maintenance interval in running hours under a PM policy, Intervention threshold	Simulation via software	Equipment manufacturing in the compressed air industry
Madu (2000)	Availability and total maintenance cost	The time between failure, The time between failure of components	DES algorithm	Mining industry
Present study	Total costs (maintenance and production)	PM intervals, Imperfect PM intervals, the number of technicians in maintenance, and buffer size	OptQuest	Automotive industry

2. Methodology

The combination of simulation and optimization is a new and powerful approach to maintenance planning problems. This approach can be applied in different ways; it depends on the simulation pattern that is selected in maintenance problems. Some simulation ways such as the Markovian process (Lam and Banjevic, 2015), DES (Roux et al., 2013, Alrabghi and Tiwari, 2016), and Monte Carlo method (Liu et al., 2016, Besnard and Bertling, 2010) can be found in maintenance problems. In this study, due to the interactions between machines and the effect of maintenance on production, discrete-event simulation (DES) is applied and implemented by the Arena simulation software package. DES is a technique representing changes and real-world behavior in industrial systems (Roux et al., 2013, Alrabghi and Tiwari, 2016).The simulation-based optimization method also allows the decision-makers to observe both the maintenance and manufacturing processes at the same time and then find the optimal decision variables. In this section, the assumptions and mathematical model in this research are defined.

2.1. Assumptions

The main model assumptions are as follows:

- The case study is a multi-product manufacturing system with different workstations and non-identical machines
- Mean Time Between Failures (MTBF) is unknown. Historical data captured over three months in the factory were used to estimate MTBF for each machine.
- PM and CM activities are scheduled in the model. Likewise, in the proposed model, PM activities will carry out imperfectly.
- To carry out maintenance activities, the production line should be stopped.
- Total costs formulated in the objective function include both production cost and maintenance cost.
- Repair time and MTBF distributions are unknown, and a tool in Arena software is used to estimate them.

2.2. Modelling manufacturing system and preventive maintenance

The optimization model, which defines the decision variables in the maintenance and manufacturing system, is mentioned in this subsection. There is a notation of variables and information used in the model.

2.2.1. Notations

Sets:

J: Set of machines in the manufacturing system- indexed by j

2.2.2. Parameters:

B_{lj}: Lower bound for buffer capacity in machine j $\in J$
B_{uj}: Upper bound for buffer capacity in machine j $\in J$
PMI_{lj}: Lower bound for PM activity interval in machine j $\in J$
PMI_{uj}: Upper bound for PM activity interval in machine j $\in J$
PMI_j: PM intervals for machine j$\in J$
HR_l: Minimum number of available technicians in the maintenance system
HR_u: Maximum number of available technicians in the maintenance system

2.2.3. Decision variables

Buf_j: Buffer capacity in machine j $\in J$

$HR\ Maintenance$: Number of available technicians in the maintenance system

2.2.4. Objective function

Z: Total cost

To optimize the maintenance and manufacturing system, the objective function should include both maintenance and manufacturing costs. As a result, the total cost formulated as follows:

$$\text{Minimize total cost} = \text{Maintenance cost} + \text{Manufacturing cost}$$

$$\text{Maintenance cost} = \text{PM cost} + \text{CM cost} + \text{labor cost}$$

$$\text{Manufacturing cost} = \text{Variable cost of manufacturing} + \text{Fixed cost of manufacturing} + \text{Holding cost at buffer}$$

PM and CM costs are evaluated per each maintenance task. Labor costs in this maintenance system concentrate on technicians' wages and are calculated per hour. In the manufacturing system, fixed costs refer to costs that do not change when output changes. However, variable cost is dependent on the number of products produced. Holding cost at buffer also refers to how much holding a unit of product costs per day. All of the manufacturing and maintenance systems' expenses were collected from prior recorded data in the factory. To define new decision variables in the problem and determine bounds for them, some discussions were conducted with experts in the manufacturing and maintenance team, respectively. In the following model, equation (1) demonstrates the objective function.

$$\text{Minimize } Z = \text{Total cost} \tag{1}$$

Subject to:

$$B_{lj} \leq Buf_j \leq B_{uj} \tag{2}$$

$$PMI_{lj} \leq PMI_j \leq PMI_{uj} \tag{3}$$

$$HR_l \leq HR\ Maintenance \leq HR_u \tag{4}$$

Constraint (2) shows the minimum and maximum of products that can be stored in the buffer and mentions buffer capacity ranges between B_{lj} and B_{uj}. Constraint (3) mentions that PM intervals range between PMI_{lj} and PMI_{uj} for machine j. In addition, constraint (4) shows available technicians in the maintenance system range between HR_l and HR_u. The optimal value for the buffer size, PM intervals, and technicians system will be determined in the simulation-optimization model.

2.3. A novel approach to model maintenance systems

Notation

T: Simulation run length

Type 1 PM: The PM activities that only control and inspect different parts of machines

Type 2 PM: In addition to inspection of the system, theses PM activities repair the broken-down parts

3. Simulation model

To simplify the industrial environment, we developed a generic simulation model in Figure 1, which involves manufacturing systems and maintenance strategies. The simulation model begins with the manufacturing system, some information such as manufacturing sequence for each product, machines' cycle time, buffers, and product's transfer time were collected and considered in the model.

3.1. Maintenance model

Required maintenance data such as maintenance cost, repair time, MTBF, and the number of technicians engaged in the maintenance system are identified in the model. Then, we considered that when the simulation runs, the simulation clock moves forward to the next event. A novel approach for maintenance modelling is presented in Figure 1. At first, it is checked if failures occur in the system, a CM activity must be carried out to repair the system. Thus, production processes are stopped, and the machine's state is changed to the inactive state. Having done CM action, the manufacturing system can start operation again.

Additionally, if any failures do not happen in the system, CM activity will be suspended until the simulation clock exceeds the MTBF. To carry out PM activities, at first, it is monitored that CM and PM do not happen simultaneously. Then, to begin a PM activity machine's state is changed to an inactive state. The type 2 PM takes more time and needs more technicians because more actions should be carried out to repair the parts. Then, having done these steps, the cost will be updated, and human resources will be released. The simulation model inputs are PM and CM cost, variable and fixed cost at manufacturing, and holding cost at buffer. The simulation model output is the total cost. Until the simulation clock reaches simulation run length, the same steps as described above are followed.

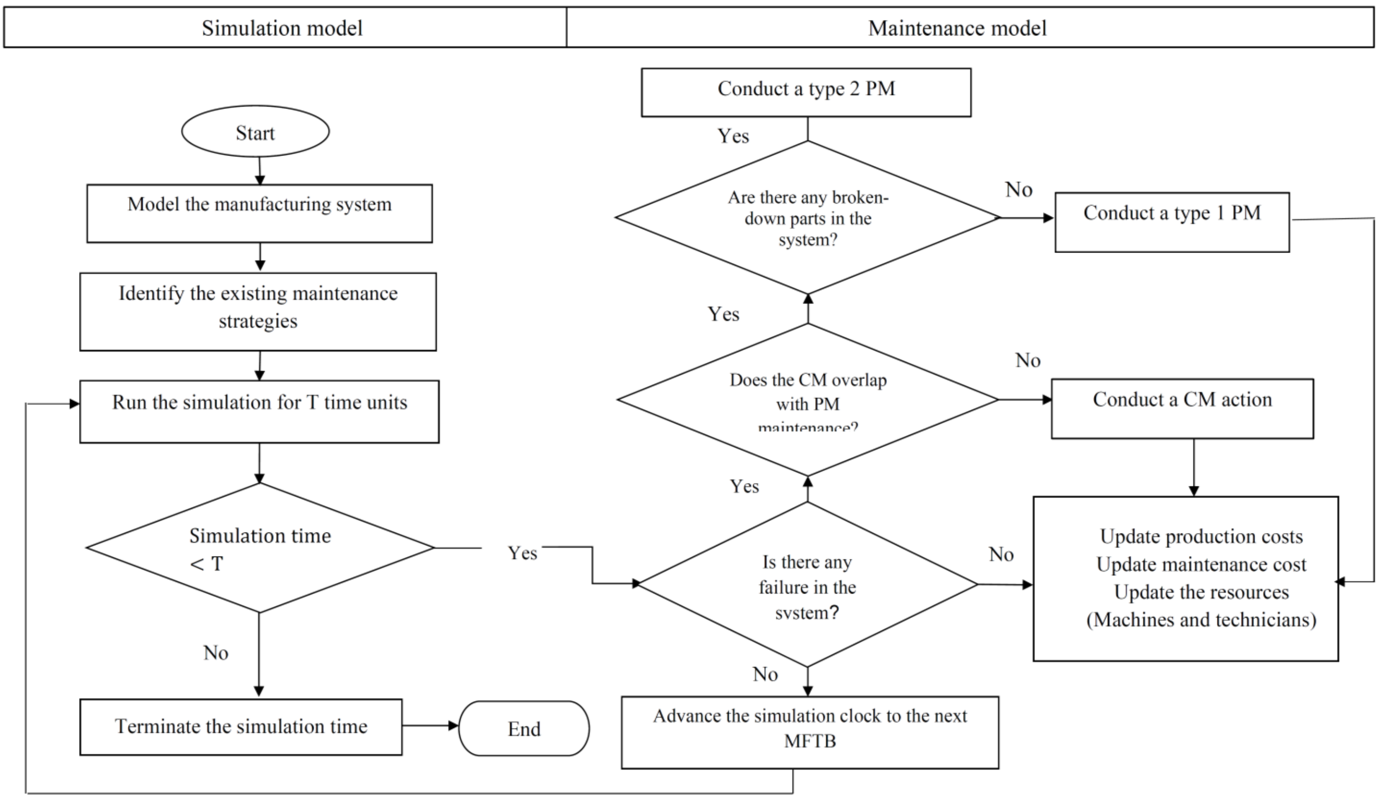

Figure 1. A generic approach to model maintenance systems

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3.2. Simulation-based optimization approach

A simulation-based optimization approach has been a common method in maintenance problems. OptQuest is a tool that can consider a series of simulations to uncover optimal or near-optimal solution scenarios. OptQuest is a generic optimizer that runs the simulation model and the optimization method separately. There are interactions between simulation and optimization procedures, enabling decision-makers to apply optimization methods in their simulation models (Nakagawa and Zhao, 2015). OptQuest uses a group of meta-heuristics, including Neural Networks, Scatter Search, Tabu search, and then combines them into a single search heuristic (Golbasi and Turan, 2020). Metaheuristics are methods, which guide other procedures (heuristic or truncated exact methods) to enable them to overcome the trap of local optimality for complex optimization problems (Glover et al., 1999). If a candidate solution does not fit the constraints, that solution is eliminated, and OptQuest explores candidates that are more likely to be better. Thanks to OptQuest, it allows users to define integer and linear constraints on the deterministic simulation inputs. It also enables users to control the search by defining different criteria. In addition, It allows different precision criteria for objective and the constrained simulation outputs. For instance, the user can specify a fixed or the number of replicates between lower and upper bounds, stopping the replication if any inferior solution is found. OptQuest also allows various stopping criteria; for example, the search can be stopped after a specific time duration or after specific non-improving solutions. We can obtain the optimal PM intervals, buffer size, and the number of technicians, using only available algorithms via OptQuest. For this problem, to create a relationship between the optimization process and simulation model, the number of replications is investigated in more detail in the optimization results section.

4. Case study and computation results

To illustrate the value of the model, an industrial case was used in the research. To find an empirical case, initial discussions were conducted to choose the most critical manufacturing line in the factory. Finally, a production line where automotive weather-stripping was produced, with high-tech machines, was selected. A case study will be explained in detail in the following sections, and the results will be argued.

4.1. Manufacturing system

The manufacturing line is a multi-product system that consists of five non-identical machines. Two types of weather-stripping are produced for a car in this production line, which we called them product A and product B. Product A is the outer weather-stripping, and product B is the inner weather-stripping that their manufacturing process is slightly different. Figure 2 shows the manufacturing process and its equipment in this factory. Both products enter the manufacturing system simultaneously, whereas product B needs an additional stage, processed by machine 5 (M5). There is a buffer after machine 4 (M4), where products are prepared for the next stage; we define its size as a decision variable. Each machine needs an operator in order to run the machine and transfer products to subsequent steps.

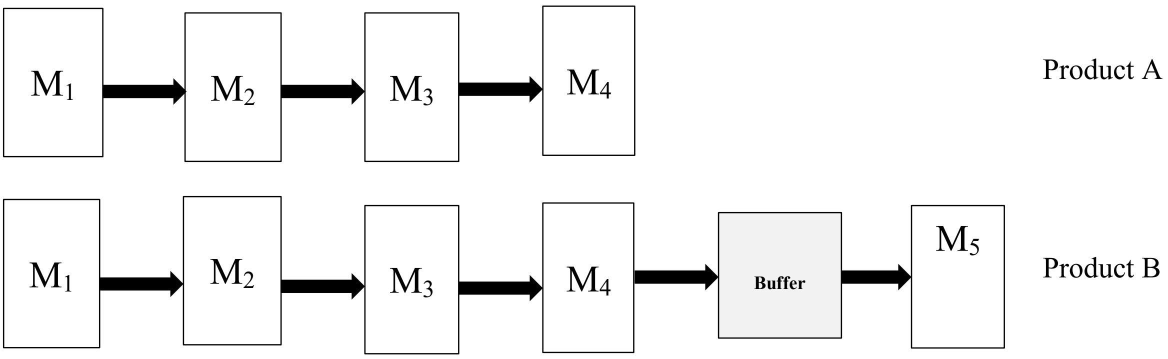

Figure 2. Production processes in the manufacturing system

The production line involves five processes as follows:

1. Injection: preformed rubber material and other chemicals are mixed in machine 1 (M1).
2. Extrusion: rubber seals are measured and cut (M2).
3. Moulding: rubber strips are moulded into particular shapes (M3).
4. Velvet insertion: rubber strips are covered with a velvet layer in machine 4 (M4). After that, rubber strips are gathered in the buffer to cool down.
5. Metal insertion: rubber strips are covered with a metal layer (M5). This process is only done for product B.

Cycle times related to each machine are given in Table 2. All machines need labor to operate.

Table 2. Cycle times for the machines in the manufacturing system

Machine	Process	Cycle time	
		Product A (minute)	Product B (minute)
1	Injection	1	1
2	Extrusion	6	11
3	Moulding	4	4
4	Velvet insertion	3	3
5	Metal insertion	-	7

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Index j that represents the machines in the manufacturing system range between 1 and 5. The manufacturing costs during the simulation are as follows:

Variable cost of manufacturing = 150000/ unit
Fixed cost of manufacturing = 200000/ set up
Holding cost at buffer = 12000/unit/hour

In the manufacturing system, the buffer capacity ranges between 600 and 880.

$$600 \leq \text{BUF} \leq 880 \tag{5}$$

4.2. Maintenance system

In the maintenance system, two maintenance strategies are carried out; PM activities considered as decision variables and CM activities. To study the maintenance system, historical data were used to fit all probability distributions. MTBF, which shows when a CM action is carried out, follows BETA. Repair times for CM and PM activities follow Triangle distribution and vary between machines. All distributions for the maintenance system are shown in Table 3. P-value is more than 0.15, which indicates the similarity between data and estimated distributions is acceptable.

Table 3. MTBF and repair time distributions in the maintenance system

Machines	MTBF (Mean Time Between Failure)*	CM repair time	PM repair time in type 1 PM	PM repair time in type 2 PM	Corresponding p-value K-S test[1]
1	25 + 48 BETA (0.0156, 0.0159)	TRIA[2](6.5, 7, 8.5)	TRIA(4.5, 5, 6.5)	TRIA(5.5, 6, 7.5)	> 0.15
2	248 + 188 BETA (0.246, 0.173)	TRIA(4.5, 5, 6.5)	TRIA(4.5, 5, 6.5)	TRIA(5.5, 6, 7.5)	> 0.15
3	258 + GAMMA (289, 0.335)	TRIA(2.5, 3, 4.5)	TRIA(4, 4.5, 6)	TRIA(4, 4.5, 6)	> 0.15
4	148 + 188 BETA (0.246, 0.173)	TRIA(8,8.5, 10)	TRIA(4.5, 5, 6.5)	TRIA(5, 5.5, 7)	> 0.22
5	87 + 102 BETA (0.192, 0.147)	TRIA(3.5, 4, 5.5)	TRIA(4.5, 5, 6.5)	TRIA(5.5, 6, 7.5)	> 0.15

*MTBF is assumed as the CM threshold in this study. In other words, after machines failed, the CM action is performed.

PM intervals (PMI) and the available number of technicians (HR maintenance) in the maintenance system are as follows:

1 Kolmogorov–Smirnov test

2 Triangular

$$10 \le PMI \le 16 \tag{6}$$

$$12 \le HR\ Maintenance \le 16 \tag{7}$$

4.3. Imperfect PM maintenance scenarios

In this research, a new approach is proposed to consider PM strategies imperfectly. The concept of imperfect maintenance refers to a maintenance operation, which leads to a system that brings to an operating state between the two extreme operating states called the 'as bad as old' and the 'as good as new' states. Consequently, to add imperfect PM strategies to the model, three scenarios are defined in Table 4. Each scenario presents the quality and accuracy of PM strategies. A weak strategy is the cheapest one, but it cannot influence failures' distribution. Weak strategy means a PM takes place with low-quality spare parts or unskilled technicians and only increases Mean Time Between Failures (MTBF) by 20 percent. However, the most expensive PM strategy, which is called high, uses the best spare parts and skilled technicians and can increase MTBF significantly.

Moreover, the average strategy is cheaper than high strategy, which provides technicians and spare parts with the quality level between weak and the high strategy. It is also assumed that imperfect maintenance has an impact on the mean time between failures. As a result, the mean time between failures is expected to increase specific amounts. We simply define α (α ≥1) coefficient that increases MTBFs; after each imperfect maintenance, the MTBF of the machines is modified to become α×MTBF. For instance, the time interval between the two failures increased by 20 percent in the weak strategy. The last PM strategy explains the current PM activities that are carried out in the industrial case study. The scenarios illustrated in Table 4, and all required data are captured from the maintenance team and management.

Table 4. Imperfect PM Scenarios based on expert's knowledge

PM scenarios	PM cost	Increase in MTBF	α	New MFTB
Weak	210000/task	20 percent	1.2	
Average	238000/task	50 percent	1.5	
High	300000/task	90 percent	1.9	$\alpha \times$ MTBF
Factory	230000/task	-	1	

4.4. Comparison of scenarios for imperfect preventive maintenance

We employed the Process Analyzer tool in Arena software to decide about three scenarios and the factory's current maintenance strategy. Table 5 illustrates controls and responses for imperfect PM maintenance scenarios in Process Analyzer. Figure 3, a result of Arena software, compares the objective function (total cost) of scenarios and shows that the Average scenario is the best PM strategy with the minimum total cost. Consequently, in the rest of the study, the Average scenario is called the proposed scenario. The following data will be optimized in OptQuest, and the findings will be compared with the current case.

Table 5. Comparison of imperfect preventive scenarios

Scenarios properties		Controls								Response
Name	Replications	PMI[M1]*[3] (Days)	PMI[M2]	PMI[M3]	PMI[M4]	PMI[M5]	α	HR Maintenance	PM cost	Total cost
Weak	20	10	10	10	10	10	1.2	13000	2100000	270501400
Average	20	12	12	12	12	12	1.5	15000	2380000	255155750
High	20	16	16	16	16	16	1.9	17000	300000	289822400
Factory	20	14	14	14	14	14	1	15000	230000	279091845

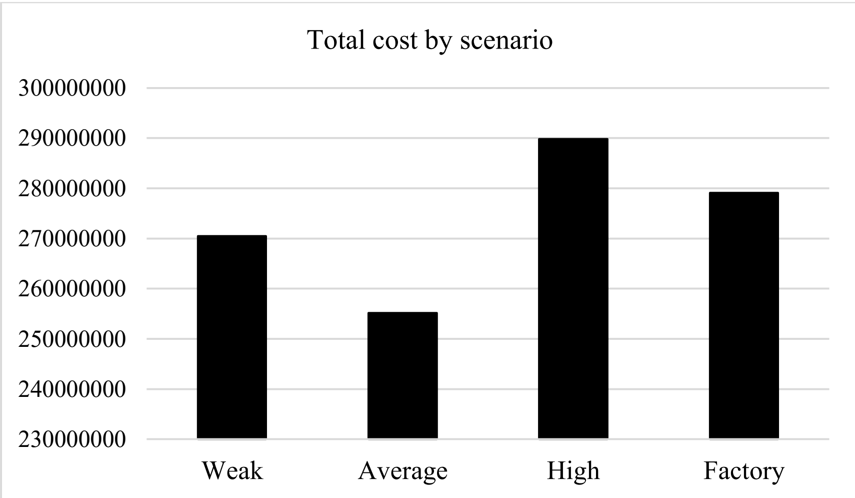

Figure 3. Comparison between scenarios and current maintenance strategy

4.5. Optimization results

The OptQuest tool in Arena simulation software package (V.14) allows the user to select special parameters and then begins to find the optimal values while simultaneously changing these parameters (Kelton et al., 2009).This tool is used to optimize the simulation model in this paper, and Table 7 show the optimal buffer size, the optimal number of technicians in the maintenance system, and the optimal PM intervals for the current model in the factory and the proposed scenario respectively.

3 PMI [M1]: PM inspection for machine 1

Table 6. The optimal solution for the current model in the factory

Decision variables	Current values in factory	Optimal values
Buffer size	652	758
HR Maintenance	15	12
PMI[M1]	14	10
PMI[M2]	14	11
PMI[M3]	14	11
PMI[M4]	14	10
PMI[M5]	14	10

Optimal total cost: 261099800

Surprisingly, if PM activities take place imperfectly, as mentioned in Table 7, this study's proposed maintenance scenario causes a significant decrease in total cost. To be precise, imperfect PM activities cause a 13.03 percent fall in the total cost function. To determine the sufficient number of replications, a 95% confidence interval of 'Total cost' is considered, then around 30 replications, the half-width achieves less than 5 million units. Hence, the number of replications is set to 30 to ensure we obtain a better estimate of 'Total cost'. The objective, the total cost is also calculated for 50 simulation runs with 30 replications. Figure 4 shows the optimization graph for the total cost associated with the case study's current model. According to the graph, the best total cost is attained at the 27th simulation, and no further change is seen.

Table 7. The optimal solution for the proposed scenario

Decision variables	Default values in the scenario	Optimal values
Buffer size	652	773
HR Maintenance	12	12
PMI[M1]	12	16
PMI[M2]	12	16
PMI[M3]	12	16
PMI[M4]	12	13
PMI[M5]	12	15

Optimal total cost: 227053900

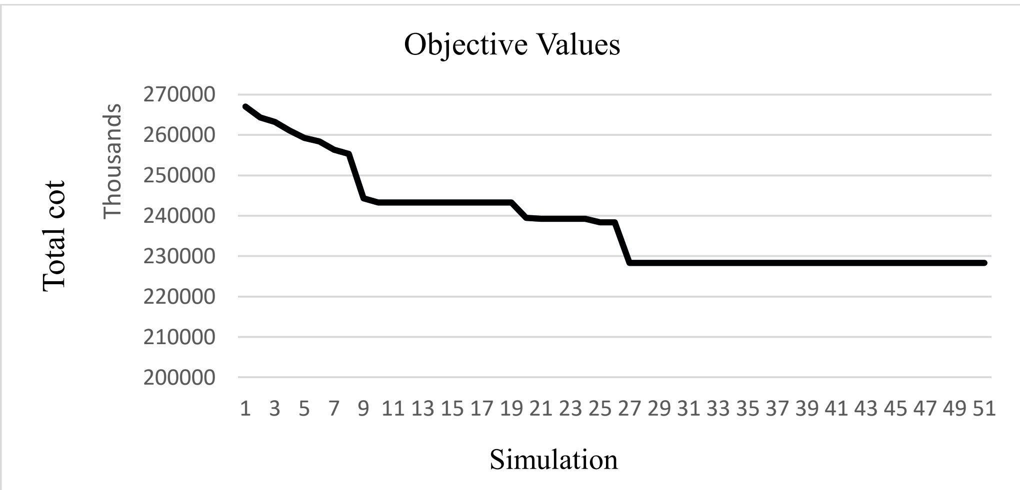

Figure 4. Optimization graph for the total cost of the current model in the factory

Furthermore, other factors, which are effective in deciding on the maintenance and manufacturing system, have been studied in the models. As seen in Table 8, wait time, WIP , and the number of waiting in the queue are extracted from the Arena software reports. To evaluate whether the differences between the current model and optimal design were statistically meaningful, 95% confidence intervals for these four factors are obtained after 30 simulations in Table 8.

Table 8. Comparative results of the simulation-based optimization method

Factors		Current design	Optimal design (proposed model)	Improvement		
				mean	Confidence interval (95%)	Significance
Wait time	Product A	295.42	294.69	0.24 %	(0.217,0.473)	Yes
	Product B	389.27	384.09	1.33 %	(0.791,1.057)	Yes
Work In Process	Product A	795.62	778.97	2.92 %	(0.294,0.451)	Yes
	Product B	5955.53	5943.14	0.208 %	(-0.215,0.107)	No
Number of waiting	Machine 1	62.1439	389.829	37.26 %	(-5.31,2.08)	No
	Machine 2	118.57	107.11	9.66 %	(0.65,0.84)	Yes
	Machine 3	38.98	28.37	27.2 %	(0.126,0.39)	Yes
	Machine 4	23.87	12.96	45.7 %	(0.146,0.935)	Yes
	Machine 5	19.36	13.02	32 %	(0.369,0.564)	Yes
Total cost		146289690	138278177	5.47 %	(0.449,2.69)	Yes

The confidence intervals confirm that the mean is statistically significant at the significance level of 0.05. As Table 8 indicates, all values are significant with the exception of WIP for product B and the number waiting for machine 1.

5. Results and discussion

Concerning the optimization results in Section 4.5, it is evident that the proposed maintenance strategy leads to a lower cost and could improve some important factors. Wait time, which shows that each product is waiting in the system, decreases by 0.24 and 1.33 percent for products A and B, respectively. After optimizing the problem, there is a decrease in the number of waiting products for product A, falling from 795.62 to 778.97; however, a decrease in WIP for product B is not statistically significant. While the number of waiting products improves in all machines, a decrease in this criterion for machine 1 is not statistically appropriate; this indicates that the number of waiting factor does not depend on the simulation-based optimization method. The total cost improvement is considerable, decreasing by 5.47%, falling from 146289690 in current design to 138278177 in optimal design. Therefore, it is shown that the proposed model and optimization approach was employed in this research can boost several factors in the maintenance and manufacturing system. Moreover, as Table 6 and Table 7 show, we find the optimal decision variables for PM intervals, the number of technicians, and buffer size by the proposed model causing a 13.03% decrease in the total cost. This paper's current approach can be used for planning maintenance activities in industrial environments with integrated production lines that a failure in a workstation may cause a full stop in the assembly line. However, based on confidence intervals, some factors did not change logically. The number waiting for machine 1, for instance, does not change after optimization, which may depend on other factors such as the machine's age since machine 1 was the oldest in our case study.

In prior studies, very little was found on discussing the scope of optimization, finding a new approach for maintenance action in a real case industry; however, this research aimed to create a simulation model and proper optimization process to address the gaps. While the majority of prior studies concentrated on mathematical models to consider imperfect maintenance activities, this paper tried to model maintenance activities by a simulation model. Although many studies in maintenance research used numerical examples to verify their model, current research developed an attempt to find an appropriate industrial case as a result; a factory that produced plastic automotive parts was selected as a case study.

6. Conclusion

This paper develops a new model to plan maintenance activities by considering the manufacturing data in industrial environments. Consequently, in addition to PM intervals and the number of technicians, buffer size was assumed to be the model's decision variables. We propose a novel approach for CM and PM activities to plan and model these activities in maintenance systems. A new assumption is carrying out PM activities imperfectly. Three scenarios were defined based on the expert's knowledge to add imperfect maintenance assumptions, and then the best scenario was selected to carry out imperfect maintenance activities in the model. The results have shown that the model can lead to a noticeable decrease in the total cost, and it offers different impacts on other factors in a manufacturing system. In addition to maintenance, data wait time, work in process, and the number of waiting were studied in the manufacturing system. Finally, after the optimization of an automotive factory, the findings support the hypothesis that maintenance improvement plays a role in boosting other manufacturing systems. There was a limitation to find a case study because only factories with high-tech machines could provide accurate information for this model; therefore, we investigated a particular factory, however; only one production line in the factory provides data for the model.

Future research can be undertaken to implement the proposed approach to other case studies with more details. For example, the spare parts management or inventory costs can be considered in future studies. Also, the equipment's age can be studied in a manufacturing system with different MTBF distribution. It is possible to formulate other functions such as reliability in the objective function and change the model to a multi-objective problem. It is also suggested that the currently proposed model can be used with other maintenance policies such as OM and CBM.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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