Identification of optimal maintenance parameters for best maintenance and service management system in the SMEs

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Abstract

Purpose – Through the use of the Markov Decision Model (MDM) approach, this study uncovers significant variations in the availability of machines in both faulty and ideal situations in small and medium-sized enterprises (SMEs). The first-order differential equations are used to construct the mathematical equations from the transition-state diagrams of the separate subsystems in the critical part manufacturing plant.

Design/methodology/approach – To obtain the lowest investment cost, one of the non-traditional optimization strategies is employed in maintenance operations in SMEs in this research. It will use the particle swarm optimization (PSO) algorithm to optimize machine maintenance parameters and find the best solutions, thereby introducing the best decision-making process for optimal maintenance and service operations.

Findings – The major goal of this study is to identify critical subsystems in manufacturing plants and to use an optimal decision-making process to adopt the best maintenance management system in the industry. The optimal findings of this proposed method demonstrate that in problematic conditions, the availability of SME machines can be enhanced by up to 73.25%, while in an ideal situation, the system's availability can be increased by up to 76.17%.

Originality/value – The proposed new optimal decision-support system for this preventive maintenance management in SMEs is based on these findings, and it aims to achieve maximum productivity with the least amount of expenditure in maintenance and service through an optimal planning and scheduling process.

Keywords Small and medium-sized enterprise, Markov decision model, Particle swarm optimization algorithm, Optimal decision-making process

Paper type Research paper

1. Introduction

In this growing competitive world, small and medium-sized enterprises (SMEs) are increasingly interested in upgrading their current manufacturing industry to a computerized and smart industry with crucial aspects such as meeting customer demand and increasing customer satisfaction and profitability. Maximum productivity, plant profitability and machine performance all depend directly on the maintenance management system factors in the manufacturing plant, so this research article will mainly focus on predicting the criticality of the individual machines, optimizing the input maintenance parameters (repair rate, failure rate) and introducing the better decision-making process of optimal maintenance and service operations in the SMEs. Individual machines' failure and repair rates are measured using a reliability-availability-maintainability (RAM) analysis tool such as the Markov Decision Model (MDM). This MDM mathematical analysis tool is an excellent analytics tool for RAM analysis because it evaluates the current variables of the machines in the manufacturing sector so that they can predict the future behavior of the machines.

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The maintenance management system is the most complex function in the manufacturing industry compared to other activities because these functions directly affect profit, smooth production running, plant productivity, etc. In the last decade, the maintenance management system has been considered the primary factor in achieving the best customer satisfaction in the competitive production world. In general, maintenance can be majorly classified into three conditions (design out, scheduled and breakdown). In this research, only the age-based maintenance (ABM) activity is considered the sub-classification of the scheduled maintenance (preventive maintenance) functions of the SME manufacturing industry. The sudden failure of the complex components in the machine will lead to a decrease in the machine's efficiency and unwanted production loss in the SME industry. The maximum availability and reliability of the complex machine components can be achieved by maintaining the scheduled maintenance function at the right time for the right ingredients in the production plant of the industry. The primary motivation of this study is to predict and classify the machines, such as the most and least critical subsystems in the manufacturing plant, based on the proposed optimal decision-making process of the maintenance management function in the industry. The categorization of the machines is carried out based on the availability variations of the particular devices. RQ1: What are the manufacturing machine's most optimal maintenance parameters to achieve maximum availability?

2. Literature review

Initially, to expand our literature review, we have included recently published research on the manufacturing and preventive maintenance upgrades of the manufacturing industry. As our study is in this context, some significant research on production and preventative maintenance schedules is considered for the degradation of critical mechanical components. We begin by presenting tasks.

Ao *et al.* (2019) explained the integrated decision model for the semiconductor production scheduling and maintenance planning with the Markov Decision Process (MDP) application and associated with MATLAB, Preventive Maintenance-plant software for demonstrating the optimal maintenance scheduling and planning operation in the industry. Similarly, Braga and Andrade (2019) described the maintenance management system of the railway wheel set problem with the application of the Markov Analysis for producing a better maintenance action (removal) compared then the existing operation based on this research analysis to estimate the damages occurrence rate of the rail wheel, bearing, etc. Likewise, Celen and Djurdjanovic (2020) explained the optimal decision-making process of the flexible manufacturing system with the communication between the maintenance and production operation by applying the partially observable MDP to propose the new model maintenance framework to the generic semiconductor manufacturing industry. Dandotiya *et al.* (2008) presented the optimal maintenance-scheduling problems in repairable line units of an aircraft fleet system to develop a new strategy for optimal decision-making of the aircraft fleet's maintenance and service management systems.

Han *et al.* (2020) describe improving the accuracy and efficiency of road maintenance operations in China using the Advanced Weight Random Forest Algorithm based on communication weight analysis and analysis sequence process to eliminate errors in decision-making considering adequate human performance. Havinga and Bram de Jonge (2020) investigated the condition-based maintenance management system in the cyclic patrolling repairman problem using the MDP to analyze the performance of the control limit policy of the system to develop the new model optimal maintenance cost function of the given scenario.

Similarly, Jin *et al.* (2020) illustrated the optimal maintenance strategy of the complex multi-state degradation system in the industry with the application of the Semi-MDP coupled with simulation techniques for producing the optimal maintenance strategy. Kamel *et al.*

(2020) illustrated the optimal solution of the multi-level integrated preventive maintenance planning and scheduling mathematical model in the chloride sodium factory by the utilization of the genetic algorithm (GA) technique with the MATLAB software through that the optimal maintenance planning and scheduling process achieved by minimizing the failure, repair, replacement and unplanned downtime cost in the industry. Lee and Pan (2020) explained the predictive maintenance (PdM) management system of the machine equipment and predicted the remaining useful life (RUL) of the machine tools with the utilization of the Discrete Time Markov Chain and the reliability, availability of the machines is measure by utilizing the Bayesian Network modeling. Liang *et al.* (2020) explained the condition-based maintenance function of the long-life asset prediction by including the environmental risk and effects in the concrete bridge maintenance by applying the Continuous-Time Semi-Markov Chain for proposing the optimal maintenance cost solution. Mishra *et al.* (2020) studied three different maintenance models with an opportunistic maintenance approach of the series-connected multiunit manufacturing system by applying the Java algorithm in the industry. Mathiyazhagan *et al.* (2019) described the critical overview of the numerous research studies on the present challenges for implementing the green concept in the sustainable manufacturing industry. Miwa and Oyama (2004) explained the optimal railway track maintenance and scheduling process by applying the integer-type linear programming model to propose the optimal and new strategy for the maintenance schedule by reducing the irregularities of the existing maintenance process in the railway track maintenance operation. Öztürk (2019) investigated the optimal inventory control problem with the industry's random supply chain management of the machine breakdown and quality inspection. Qiang *et al.* (2020) demonstrated the minimum and optimal vehicle route problems for the gold chain logistic distribution with the application of the greed search algorithm. Reddy *et al.* (2020) established the new model framework for the heart disease diagnostic process by using the adaptive GA with the fuzzy logic technique to predict heart disease at an earlier stage and reduce the risk of death and cost of the treatment. Srivastava *et al.* (2020) described the maintenance issues in the sugar plant and analyzed the existing strategies of maintenance planning through the application of three different multi-criteria decision-making (MCDM) approaches for implementing the optimal maintenance scheduling and planning of the sugar plant.

Likewise, Sanusi *et al.* (2020) demonstrated the industry's performance evaluation of the series and parallel manufacturing systems. The availability of the systems is analyzed and investigated based on the maintenance parameters (failure rate and repair rate) by using the Markov Model with the first-order differential equations mathematical analysis to produce the optimal result for the given manufacturing industry. Sharma and Vishwakarma (2014) illustrated the performance analysis of the sugar-producing sector with the application of the MDP, based on this research, to propose the optimal maintenance policy and identified the complex repairable system in the given manufacturing plant. Sun *et al.* (2020) explained the manual and automatic designing algorithm of the conventional neural network (CNN) technology for the image classification process by the application of the GA techniques and the optimal solution of the manual and automatic designing architecture of CNN to the image classification problems in the industry. Tewari and Malik (2016) explained the critical overview of the numerous research articles on availability analysis of the thermal power plant and its real-time case studies through the application of the Markov model mathematical analysis techniques.

In the same way, Velmurugan *et al.* (2019a, b) described the RAM analysis of the manufacturing industry and the optimal maintenance policy of SMEs through the utilization of the Markov Birth Death process. To propose the new maintenance framework, with the maximum availability of the given manufacturing process, and identify the most critical machine components based on the availability variation in the industry, Vikrant and Goyal

(2016) demonstrated the analysis of the availability changes in the paper-making manufacturing industry through the application of the Markov model technology with the GA technique for identifying the optimized maintenance parameters to achieve the maximum availability of the manufacturing system in the paper-making industry. Velmurugan *et al.* (2021a, b) described the performance analysis of the tire manufacturing industry to implement the optimal maintenance decision-making process and organized a new model of the intelligent maintenance management system through the application of the machine learning algorithm in the manufacturing industry. Zhou *et al.* (2020) illustrated the evaluation of the RUL of the supercapacitors used in the electric motors of the vehicles by using the hybrid method of GA and recurrent neural network (RNN), the optimal RUL of the supercapacitors predicted for gaining the better availability, reliability and validity of the product. Based on these various research articles, the analytical techniques available using MDP to achieve optimal maintenance management systems for small and medium-scale manufacturing industries were understood. Saihi *et al.* (2022) described the detailed systematic literature reviews of the maintenance management system and the sustainability modeling in the industry. Through these overviews, the integrations of the issues in the sustainability modeling and other maintenance management systems for the better optimization process of manufacturing industries the critical overviews of the total productive maintenance (TPM) strategies were illustrated briefly by Chaurey *et al.* (2023). This empirical research study found a larger research gap in the development strategies of TPM in the manufacturing sectors. Similarly, Singh and Gurtu (2022) dealt with prioritizing the success factors influencing the development and implementation of the TPM strategies in the manufacturing industries. Based on this, research outcomes improve the involvement of the top-level management teams in the TPM implementations and encourage the employees to achieve the maximum productivity in the manufacturing industries. The different industries with 13 real-time industrial case studies in the field of the PdM management system have been explained by Tiddens *et al.* (2022). The Industry 4.0 technologies for the smart and PdM management system were studied and implemented in the outcome of this research in the manufacturing industries cited in the Netherlands, The clear overviews and optimal methodology for the implementation process of the PdM management strategies in the manufacturing industries were explained in the basic levels in this industrial case studies. Algabroun *et al.* (2022) explained the digitalized maintenance management concept for the smart manufacturing industries, identified the present critical factors in the digital maintenance management strategies implementation in the industries through this research and provided a better solution to the current issues in maintenance management. Bashar *et al.* (2022) illustrated the actual linkages between people management and TPM strategies in the manufacturing industries by conducting real-time empirical research studies in various manufacturing industries. The significant outcome evidence of this industrial case research has been proven and implemented in the working environment of the manufacturing industry. Avakh Darestani *et al.* (2022) dealt with the design and development of the optimal decision-making strategies for a better maintenance management system in the industry. Two different approaches were integrated to identify the better solution to the optimal decision-making issues in the maintenance department. The goal programming was developed for the optimal decision-making dashboard with the outcome of the MCDM method (Best-Worst Method, TOPSIS) for prioritizing the factors influencing the optimal maintenance management system. They are widely used in the manufacturing process of single-machine failure constraints. It has been identified that no such available research from a previous research article has reported more than one machine failure simultaneously in the manufacturing plant. To fill the research gap of specific research articles, frame the following problem descriptions.

3. Notations

The various notations used for this optimization analysis research in the maintenance management system of the pressing part production plant are given below.

A	Lancing machine.
B	Welding machine.
C	Ground inserting machine.
D	End-of-line testing machine.
A, B, C, D	Good state of the machines
$\underline{a}$, $\underline{b}$, $\underline{c}$, $\underline{d}$	Under-repair state of the machines
*a, *b, *c, *d	Failed state of the machines
λ_M	Rate of failure (M = A, B, C, D, A&B and C&D).
μ_M	Rate of repair
ϕ_M	Rate of transition
η_M	Rate of preventive maintenance
x	Constant (0 for ideal and 1 for faulty)
P_0 (t)	Probability functions of all machines are in good condition
$P_i(t)$	Probability functions of the respective machines are in a under-repair state (i = 1, 3, 5, 7, 9 and 11).
$P_j(t)$	Probability functions of the respective machines are in the failed state (j = 2, 4, 6, 8, 10 and 12).

3.1 Assumption

This research article's availability analysis of the critical part production maintenance model confirms the following assumptions.

(1) Initially, every production machine is in good condition (A, B, C and D).

(2) The rate of repair and failure of every production machine is constant and statistically independent (λ_M, $\mu_{M=}$Constant) (M = A, B, C and D)

(3) Every repaired production machine is assumed to be as good as new.

(4) The unique maintenance team members handle the maintenance and service activities of the system.

(5) Every production machine has three states: good, under repair and failed (ex: A, $\underline{a}$ and *a).

(6) Only the defined simultaneous failures of the production machines are considered, such as A & B and C & D.

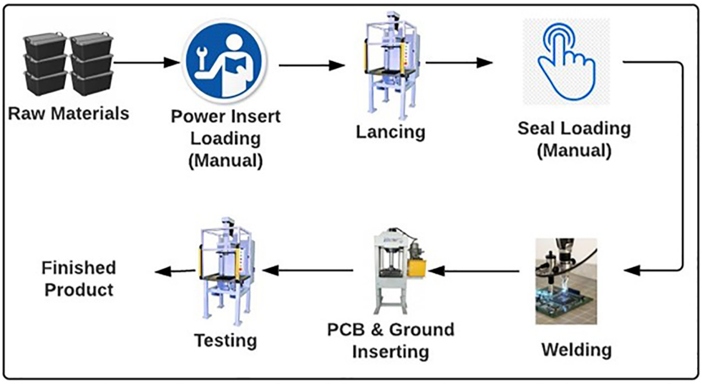
(7) The PM and the transition rate are considered constant (η_M, ϕ_M = Constant).

4. Problem description

Small and medium-scale manufacturing industries face many challenges to achieve maximum productivity, customer satisfaction, planning and scheduling the proper preventive maintenance activity. This research aims to analyze the real-time maintenance problems in one of the SMEs in the southern region of Tamil Nadu, India. Here increased production delay time, machine downtime and reduced product quality predominantly occurs due to unplanned maintenance activity and an improper workforce of the maintenance team in the manufacturing plant. Because of that, this research focuses on analyzing the present maintenance function concerning the maintenance record data of daily production in the SMEs involved in this analysis research and organizing a better decision-making process for the optimal planning and scheduling of the service and preventive maintenance functions in the SMEs. The most important features of this analysis study are as follows: (1) analyze the maintenance management problems of the manufacturing plants by the actual time industrial case study. (2) The critical subsystems of the manufacturing plant have been identified through the availability variations of the individual systems with the utilization of the MDM. (3) Initially, the optimal maintenance parameters (failure and repair rates) are predicted for the better decision-making process of the maintenance management systems through the application of the particle swarm optimization (PSO) algorithm. In the future, this proposed optimal prediction has been compared with the most widely used heuristic algorithm for achieving the suitable and most significant solution for the smart preventive maintenance management system in the industry. The main objective of this research analysis is to implement the optimal decision-support system that minimizes the maintenance investment cost and machine downtime and maximizes the effectiveness of the maintenance team and productivity. The manufacturing system of the critical part production flow process is briefly described below.

4.1 Real-time industrial case study

The small and medium-scale sensor and switch medium-scale plant (XYZ Private Limited, Madurai) in the southern part of Tamil Nadu, India has been selected in this industrial case study. The electronic component carrier (ECC) is the most critical assembly part of the automobile vehicle production industries. These parts are mainly used for the automatically controlled window mirror function in the latest technology of automobile vehicles. The SMEs' complex systems have been investigated in this critical part of the manufacturing flow process. These production units operate the three-shift (working time) due to the higher demands of the customers. This integral part has six sequences of the manufacturing flow process as shown in Figure 1. The detailed description of the essential part manufacturing process is explained below.



Note(s): Figure 1 is never adapted from anywhere genuinely prepared by first author of this manuscript based on the real time industrial manufacturing process, so we are only the original IP of this figure

Figure 1. Manufacturing flow process of the critical part production

4.2 Manufacturing system description

Power insert pressing preparation: Initially, the signal conducting pin is placed correctly on both sides (left-hand side and right-hand side) of the given critical part plastic mold by the manual operating method. After completing this process, it will move to the next manufacturing operation.

Lancing and circuit testing: In the lancing operation (Machine A), the prepared critical part plastic mold placed in the pneumatic pressing machine for the signal conducting pins are fixed in the required height by applying the 4–6 bar compressive force then the traces are created to the signal conductivity process. They are finally checking the quality of the critical part's circuit signal conductivity. These three operations are carried out simultaneously using a single machine (Power Insert Pressing Machine) with a minimum cycle time (7.11 Sec/ Part). After completing the operation, this product will move the further manufacturing process to the shop floor area.

Brush routing/spring and seal loading: In this manufacturing process, the spring, brush routing and joined seal are placed in the proper direction of the critical part plastic mold by the manual operation method with the utilization of the assembly fixture after finished the operation this product will move to the other manufacturing flow process.

Brush braid welding: In the brush braid welding process (Machine B), the assembled brush routing and spring are welded on both sides (left-hand side and right-hand side) of the critical part plastic mold by the utilization of the top and bottom copper electrode and automatic welding machine with the minimum cycle time (15.43 Sec/Part) after completing the operation this product will move the further manufacturing process in the shop floor area.

Printed circuit board (PCB) and ground inserting: In this manufacturing process (Machine C), the programmable circuit board and ground plates are fixed in the proper direction of the critical part plastic mold to control the action of the actuator/switches in the ECC by the utilization of the PCB pressing machine with 4–6 bar compressive force. This operation completes the minimum cycle time (7.5 Sec/Part). After the procedure, this product will move to the other manufacturing flow process.

End of line testing (EOL): In the EOL testing process (Machine D), check the resistance, impedance and quality of the final product by the utilization of the resistance and impedance testing machine with the specific tools and fixture after completing the entire manufacturing process this critical part will move to the firewall inspection then packing the finished part goods to the customers.

In this critical part manufacturing model, the four machines (A, B, C and D) are operated during the process. The service and maintenance policy of each device depends on the maintenance parameters (λ, μ, ϕ and η) of machine components. The maintenance problem is to develop the optimization of the availability and reliability of the critical part production model, which considers the prediction of the maximum availability of the given manufacturing system to achieve full benefits (profit and customer satisfaction) in SMEs. The availability and reliability analysis of the critical part production model is to be determined in the following sections. Initially, the notations and assumptions used for implementing the availability equation of the essential part production model are described.

5. Mathematical modeling

The availability (Av) of the critical part production systems in the small and medium-scale farming industry was analyzed with the application of the MDP. To identify the future behavior of the complex machine components based on the present maintenance parameters (failure and repair rates) of the individual machines in the given manufacturing system of the SMEs. This MDP generates the availability prediction equations using the manufacturing system's transition state diagram (TSD). This TSD developed with three state conditions (good, maintenance and failed) of the individual manufacturing machines in the SMEs. Figure 2 shows the TSD of Machine A. The TSD of the critical part production system is shown in Figure 3. The sample transition state analysis and the formulation of the availability prediction of Machine A have been illustrated below.

Machine A consists of the three different states of the transition condition such as State 0: original or good, State 1: under maintenance and State 2: failed. The transition state of the individual state is described in the sample TSD model, and the equation generation of the individual state probability condition has been derived below.

State 0: This condition considers the original state or good condition of the machine.

State 1 (under maintenance): In that situation, Machine A starts the transformation from state 0 to state 1 (original condition to under maintenance). The state 1 probability condition [$P_1(t)$] concerning the time and formulations is expressed below through the application of the MDP.

$$\eta_A P_1(t) = \phi_A P_0(t) \tag{1}$$

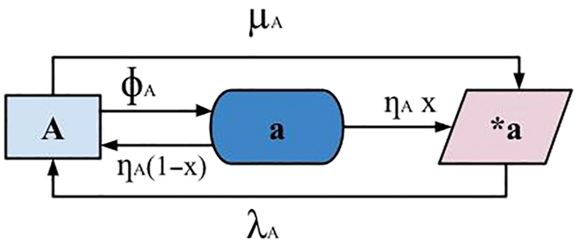
State 2 (failed): In these conditions, Machine A transforms from state 1 to state 2 (under maintenance to failed). The probability condition [$P_1(t)$] equation of state 2 with the utilization of the MDP and consideration of the time has been illustrated below.

$$\mu_A P_2(t) = \eta_A x P_1(t) + \lambda_A P_0(t) \tag{2}$$

Similarly, derive the equation of the individual machine in the manufacturing plant and summation of all the state probability state conditions for prediction of the availability of the whole manufacturing plant. The generalized formulation of the critical part manufacturing system has been clearly explained in the following subsections.

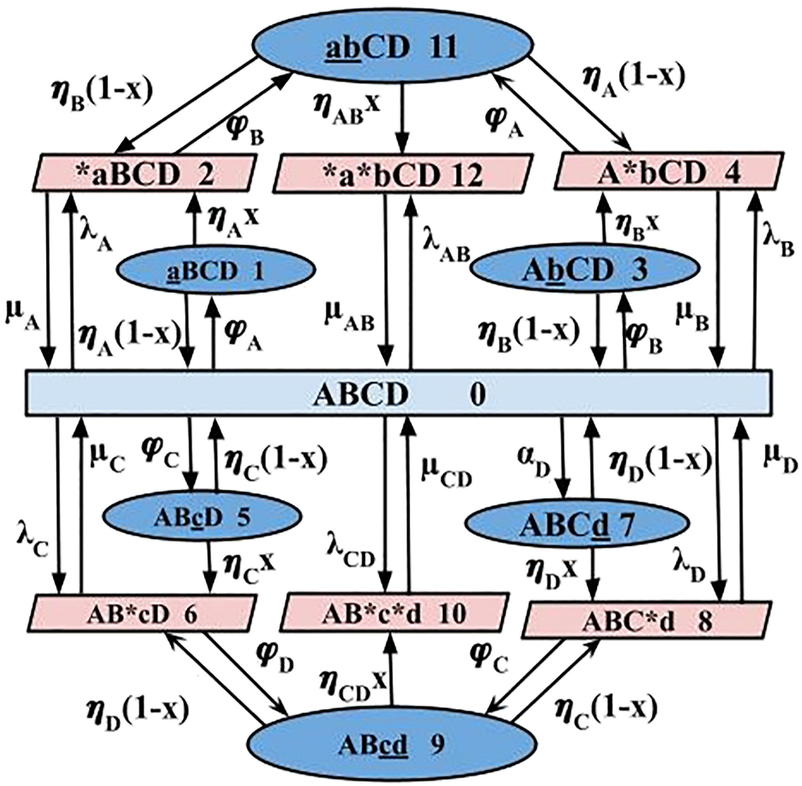
5.1 Formulation of the availability prediction of the manufacturing system

The probability function of the machines in the critical part production system has initially started the transformation from an excellent state to an under-repair state. The mathematical representation of the MDM equation is given below.



Note(s): Figure 2 is similar model of one of our manuscripts that adopted from the manuscript Velmurugan, K., Venkumar, P. and Sudhakarapandian, R. (2021) Performance Analysis of Tyre Manufacturing System in the SMEs Using RAMD Approach. Mathematical Problems in Engineering, doi.org/10.1155/2021/6616037

Figure 2. Sample TSD of the Machine A



Note(s): Figure 3 is similar model of one of our manuscripts that reprinted from the manuscript Velmurugan, K., Venkumar, P. and Sudhakarapandian, R. (2021) Performance Analysis of Tyre Manufacturing System in the SMEs Using RAMD Approach. Mathematical Problems in Engineering, doi.org/10.1155/2021/6616037

Figure 3.
TSD of the critical part production system

$$\eta_M P_i(t) = \phi_M P_0(t) \tag{3}$$

The probability function of the machines in the critical part production system has started the transformation from an under-repair state to a failed state. After the maintenance and service activities, production machines are restored to good condition. The mathematical representation of the MDM equation is explained below:

$$\mu_M P_j(t) = \eta_M x P_i(t) + \lambda_M P_0(t) \tag{4}$$

5.2 Steady-state probability condition of the critical part production model

The critical part manufacturing process of all systems (A, B, C and D) is considered to be in a steady-state condition. In that situation, the transition time of all the critical part production systems is assumed to be zero, which means $t = 0$.

The steady-state condition is applied to the above Av measuring equations (3-4). Finally, we get the steady-state probability equations of the critical part production systems described below.

$$\frac{d}{dt} \to 0 \text{ as } t \to \infty \text{we get,}$$

$$\eta_M \mathrm{P}_i = \phi_M \mathrm{P}_0 \tag{5}$$

$$\mu_M \mathrm{P}_j = \eta_M x \mathrm{P}_i + \lambda_M \mathrm{P}_0 \tag{6}$$

The above equations (5-6) are solved recursively, and we get,

$$\mathrm{P}_i = D_i \mathrm{P}_0, \mathrm{P}_j = D_j \mathrm{P}_0 \tag{7}$$

Where.

i = 1, 3, 5, 7, 9 and 11,
j = 2, 4, 6, 8, 10 and 12.

The steady-state probability equations of the critical part production systems are described and then apply the normalizing condition of the above Av measuring equations (5-6). The sum of all the probability functions of the critical part production system is equal to 1. This normalized condition equation is explained below.

Using normalizing condition

$$Av = 1$$

$$\left(1 + \sum_{k=1}^{6} P_{(2k-1)} + \sum_{k=1}^{6} P_{2k}\right) P_0 = 1 \tag{8}$$

$$P_0 = \left[1 + \left(\sum_{k=1}^{6} P_{(2k-1)} + \sum_{k=1}^{6} P_{2k}\right)\right]^{-1} \tag{9}$$

where

$$\mathrm{k} = 1, 2, 3, 4 \ldots 12$$

$$A_v = p_0 \tag{10}$$

The given (Table 1) input numerical data were collected and pre-processed from the real-time maintenance data sheets or previously recorded maintenance and service actions data of the individual machine in the production plant of the selected manufacturing industry cited in the southern region of Tamil Nadu, India. This real-time case study research mainly focused on the failure rate and repair rate prediction of the individual machine has been measured. The

Machine	Failure rate (λ)	Repair rate (μ)	Transition rate (ϕ)	Preventive maintenance rate (η)
Machine A	0.025	0.150	0.007	0.12
Machine B	0.020	0.138	0.001	0.17
Machine C	0.029	0.290	0.005	0.35
Machine D	0.026	0.158	0.004	0.12
Machine A&B	0.022	0.144	0.008	0.15
Machine C&D	0.027	0.224	0.009	0.24

Note(s): The Table 1. Reprinted from our manuscript (Velmurugan *et al.*, 2021a), Performance analysis of tire manufacturing system in the SMEs Using RAMD approach. *Mathematical Problems in Engineering*, doi.org/10.1155/2021/6616037

Table 1.
Input numerical values (maintenance parameters) of a critical production system

sample calculation of the raw data pre-processing and the input maintenance parameter prediction have been explained below.

Initially, the previous year's machine maintenance record data have been collected from the industry through the maintenance department. The raw data consist of the actual data of the individual machines such as utilization time, break time, maintenance time and idle time, etc. From these raw data, necessary input maintenance parameters (failure and repair rates) were pre-processed.

The failure rate of the machine has been pre-processed by the utilization time of the particular machine and the number of failures during the working period, simply defined as the ratio of the total number of failures that occur to the actual usage of the machine. For example, Machine A occurs 216 times of failure within the selected time duration denoted as the (F) and the total that machine utilized for 8,640 h (Twenty-four hours * Thirty days* Twelve months) denoted as (UT). In that production plant, the failure rate of Machine A mathematically expressed as given below.

$$\text{The failure rate of Machine A} = \frac{\text{Number of failures (F)}}{\text{Total utilization time (UT)}} = \frac{216}{8640} = 0.025 \tag{11}$$

Similarly, the repair rate of the machine has been pre-processed based on the real-time maintenance record sheets data such as total maintenance time (MT) and the number of failures that occurs during the given production period. Generally, it's defined as the ratio between the numbers of failures (F) to the total MT of that machine. For example, the total maintenance or service time (MT) of a machine is 1,440 h (Twenty-four hours * Five days* Twelve months). In that manufacturing plant, the repair rate of Machine B has been mathematically expressed as given below.

$$\text{Repair rate of Machine A} = \frac{\text{Number of failures (F)}}{\text{Total maintenance time (UT)}} = \frac{216}{1440} = 0.150 \tag{12}$$

Likewise, it pre-processed all other machine maintenance parameters (failure and repair rates) of the selected manufacturing plant. In this optimization, the analysis considers only the above-mentioned parameters (failure and repair rates) that were pre-processed through the real-time maintenance data in the industry. Other than these, two parameters were applied from the benchmark problems of the research article.

6. Availability analysis by using particle swarm optimization algorithm

This research article utilized the most widely used nontraditional optimization techniques for predicting the optimal solution of the given manufacturing system in SMEs. The PSO algorithm is an effective computerized search tool for identifying the best and optimal solution to complex engineering problems based on genetic and neural selection mechanics, as shown in Figure 4. The function of PSO is to optimize the maintenance parameters (availability, failure rate, repair rate and preventive maintenance rate) to get optimal solutions for the given manufacturing systems in SMEs. The pseudo code for the proposed PSO and the operating procedure of the optimization approaches is given as follows:

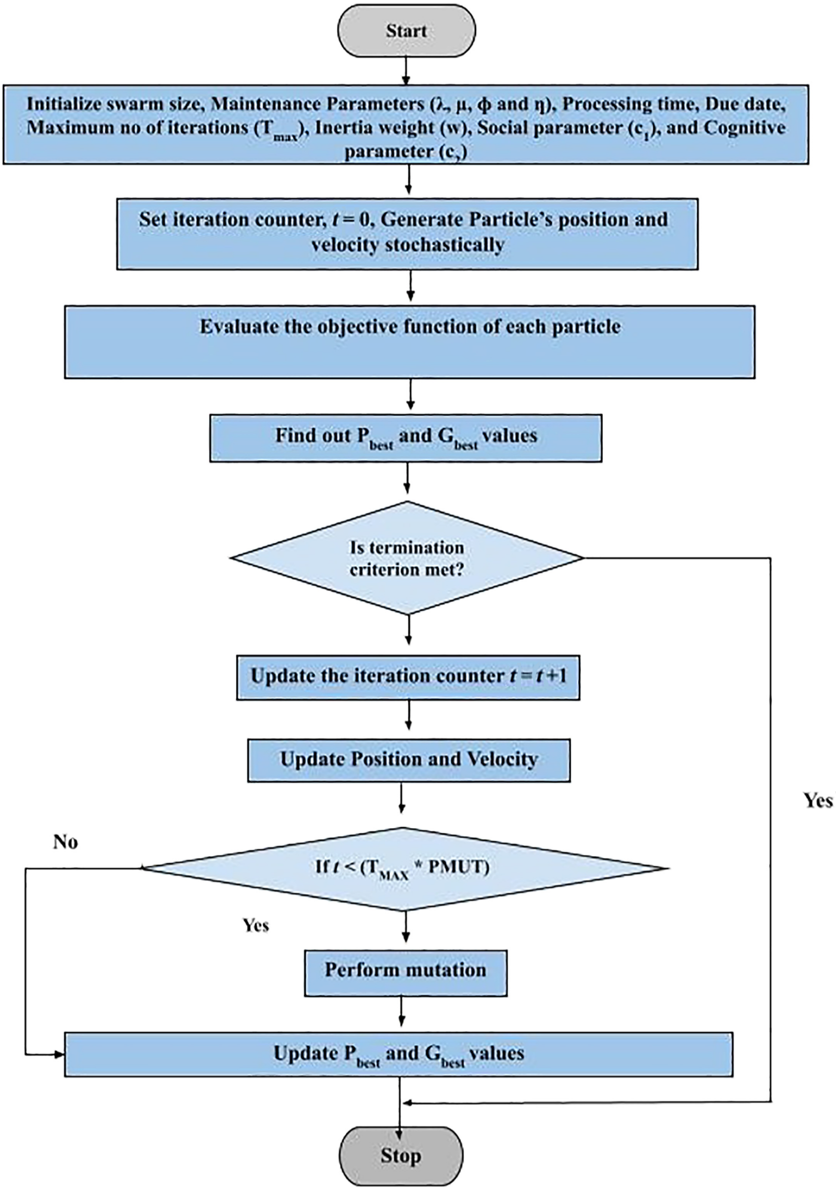


Figure 4.
A typical framework for the particle swarm optimization algorithm technique

Note(s): Figure 4 was genuinely prepared based on the standard flow process of the optimization techniques with our own constraints through the first author of this manuscript, It never adopted from anywhere

Pseudo Code:

Initialize the maintenance parameters (λ, μ, ϕ, and η), including swarm size, the maximum number of iterations, w, c_1, c_2

While (termination condition, i.e., maximum Iteration)

Do

t=**0**

Initialize the particle's position and velocity stochastically.

Evaluate each particle's fitness, i.e. the objective function;

Initialize P_{best} position.

Initialize the G_{best} position with the particle with the lowest fitness in the swarm.

t= t+1;

Update the velocity of the particles by the equation (15);

Update the position of the particles by the equation (16);

Evaluate each particle's fitness, i.e., the objective function.

Perform mutation when t < (T_{max} * PMUT); (where T_{max} is the maximum number of iterations, PMUT is the probability of mutation)

Find the new G_{best} and P_{best} values by comparison.

Update G_{best} of the swarm and P_{best} of each particle.

end do

end.

Procedure:

Step 1: Initialize the parameters (λ, μ, ϕ, and η) and a number of particles.

Step 2: Set the iteration numbers t=0+1=1,

Step 3: Set the initial velocity of all particles as zero.

Step 4: Compute the Personal best for each particle.

$$P_{Best,i}^{t+1} = \begin{cases} P_{Best,i}^{t+1}, & if\ F_i^{t+1} > P_{Best,i}^{t+1} \\ X_i^{t+1}, & if\ F_i^{t+1} \le P_{Best,i}^{t+1} \end{cases} \tag{13}$$

Step 4: Measured the Global best for each particle.

$$G_{best} = min\{P_{Best,i}^{t+1}\} \tag{14}$$

Step 5: Find the velocity of each particle and consider the random number 0, 1. In that situation consider two different state conditions like faulty and ideal conditions of the machine.

$$V_i^{t+1} = V_i^t + c_1 r_1^t\{P_{Best,i}^t - X_i^t\} + c_2 r_2^t\{G_{best} - X_i^t\} \tag{15}$$

Step 6: Compute the new value of X_i.

$$X_i^{t+1} = X_i^t + V_i^{t+1} \tag{16}$$

Step 7: Measured the Objective function F_i

Step 8: Repeat step 2 to step 7 and increased the iteration number (t=1+1=3) until the best and optimal solutions are reached with optimal objective functions.

The performance of the critical part production systems is purely dependent on the failure rate, repair rate, preventive maintenance rate and transition rate of each system in the SMEs as shown in Table 1. These maintenance parameters ensured the performance of the critical part production system. This PSO is proposed to optimize the maintenance parameters (λ, μ, ϕ and η) of the critical part production system under ideal and fault conditions. The number of parameters is twenty-four (six failure parameters, six repair parameters, six PM parameters and six transition parameters). The unsigned fixed point integer coding maintenance parameters (λ, μ, ϕ and η) mapped into a specified range [LP_{Min}, UP_{Max}] where LP_{Min} and UP_{Max} are the lower points and upper point maintenance parameters (λ, μ, ϕ and η) values of the critical part production system in SMEs. The best and optimal values of the fitness function (Av) correspond to the maximum input maintenance parameters (λ, μ, ϕ and η) values of the given manufacturing system. These maintenance parameters are optimized, according to the maximum Av of the critical part production systems in SMEs, to evaluate the manufacturing system Av by the proposed PSO with the different particle sizes and a number of iterations and predict the optimal solution of the maintenance parameters (λ, μ, ϕ and η) with the unit availability situation.

The Av changes of the critical part production system in faulty condition with initial particles ranging from 30 to 300 are shown in Table 2. The maximum Av reached maintenance parameters (λ and μ) are highlighted. The size of particles is gradually increased by 30 intervals from 30 to 300 ranges. The Av changes of the critical part production system in ideal condition with particles ranging from 30 to 300 are shown in Table 3. The maximum Av reached particles and maintenance parameters (λ and μ) are highlighted and the graphical illustration of the Av changes of both fault and ideal conditions is shown in Figure 5. The horizontal axis denotes the number of particles and the vertical axis represents the Av of the manufacturing system. In a faulty and ideal condition, Av of the manufacturing system variations typically occurs concerning the distribution of particular machine maintenance parameters (λ, μ, ϕ and η). From the pictorial representation, the maximum Av of the manufacturing system has been identified, such as 73.30% in the faulty state and 77.93% in the ideal state. The corresponding optimal machine maintenance parameters (λ, μ, ϕ and η) are listed in Table 6 and Table 7. This availability of the system and the maintenance parameters variations solutions are compared with the previously published research articles (Sharma and Vishwakarma, 2014).

The optimal Av reached (N = 180) maintenance parameters (λ, μ, ϕ and η) are further analyzed with the various iteration range from 10 to 100 to measure the Av changes and justify whether that size of particles (180) output results of the PSO is satisfy the requirement of the maintenance department in the SMEs. The Av changes of the critical part production system in faulty condition with iteration range from 10 to 100 are shown in Table 4. The Av changes of the critical part production system in ideal condition with iteration range from 10 to 100 are shown in Table 5. The pictorial representation of faulty and ideal conditions is shown in Figure 6. The horizontal axis denotes the number of iterations and the vertical axis represents the Av of the manufacturing system. In a faulty and ideal condition, Av of the manufacturing system variations occurs normally based on the distribution of machine maintenance parameters (λ, μ, ϕ and η). From the pictorial illustration, the maximum Av of

Faulty (X = 1) Parameters			Failure rate λ_A	λ_B	λ_C	λ_D	Repair rate μ_A	μ_B	μ_C	μ_D
N	Av	P_{max}	0.065	0.040	0.069	0.066	1.150	1.138	1.290	1.158
		P_{min}	0.025	0.020	0.029	0.026	0.150	0.138	0.290	0.158
30	0.6358		0.0475	0.0541	0.0463	0.0447	1.0625	0.9243	0.4171	1.0519
60	0.6399		0.0329	0.0422	0.0335	0.0492	0.7114	1.0358	1.0548	0.9600
90	0.6927		0.0423	0.0368	0.0402	0.0307	0.7260	1.0495	1.2299	1.1321
120	0.6773		0.0359	0.0589	0.0423	0.0393	0.5128	0.9732	1.0988	0.7350
150	0.6632		0.0615	0.0441	0.0478	0.0556	0.9999	0.9527	1.2484	0.7233
180	*0.7331*		*0.0498*	*0.0254*	*0.0448*	*0.0493*	*0.8102*	*0.7942*	*1.0108*	*1.0939*
210	0.6777		0.0339	0.0555	0.0434	0.0393	0.8532	1.0211	0.6274	1.1223
240	0.6969		0.0315	0.0424	0.0346	0.0492	0.7231	0.8783	0.9130	1.0362
270	0.6980		0.0336	0.0286	0.0456	0.0479	0.9705	1.0094	1.2533	0.9903
300	0.6906		0.0277	0.0216	0.0601	0.0325	0.5109	0.3502	1.0362	1.0235

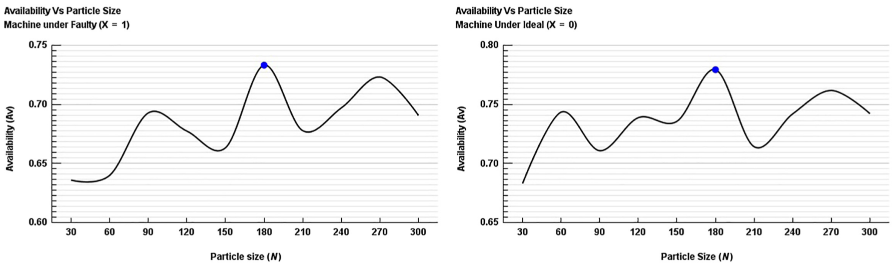
Note(s): Table 2 was originally generated based on the actual results of optimization and analysis technique through the first author of this manuscript. It never adopted from anywhere

Table 2.
Effect of Av changes in the particle size variations with the faulty condition

Ideal (X = 0) Parameters			Failure rate λ_A	λ_B	λ_C	λ_D	Repair rate μ_A	μ_B	μ_C	μ_D
N	Av	P_{max}	0.065	0.040	0.069	0.066	1.150	1.138	1.290	1.158
		P_{min}	0.025	0.020	0.029	0.026	0.150	0.138	0.290	0.158
30	0.6830		0.0278	0.0392	0.0464	0.0655	1.1280	0.4490	0.9149	1.1536
60	0.7434		0.0616	0.0260	0.0571	0.0387	0.9872	1.0573	0.8142	1.0988
90	0.7107		0.0452	0.0218	0.0392	0.0400	0.7446	0.9028	0.8592	0.6988
120	0.7387		0.0324	0.0256	0.0414	0.0529	0.7740	0.9488	0.8690	0.9600
150	0.7356		0.0270	0.0537	0.0308	0.0376	0.9608	0.6417	1.1467	1.1370
180	*0.7793*		*0.0319*	*0.0252*	*0.0502*	*0.0403*	*0.7280*	*1.0348*	*0.9902*	*1.0470*
210	0.7141		0.0283	0.0428	0.0491	0.0305	0.4326	1.0974	0.9844	0.7331
240	0.7419		0.0325	0.0336	0.0486	0.0283	0.6038	0.7972	1.0832	0.8270
270	0.7617		0.0396	0.0230	0.0476	0.0465	0.8483	0.7551	0.6910	1.0216
300	0.7421		0.0301	0.0588	0.0358	0.0563	0.9715	1.1268	0.8602	0.6186

Note(s): Table 3 was originally generated based on the actual results of optimization and analysis technique through the first author of this manuscript, It never adopted from anywhere

Table 3. Effect of Av changes in the particle size variations with the ideal condition



Note(s): Figure 5 was genuinely prepared based on the analysis result through the first author of this manuscript, It never adopted from anywhere

Figure 5. The effect of Av and particle size variation in faulty and ideal conditions

Faulty (X = 1) Parameters			Failure rate λ_A	λ_B	λ_C	λ_D	Repair rate μ_A	μ_B	μ_C	μ_D
NI	Av	P_{max}	0.065	0.040	0.069	0.066	1.150	1.138	1.290	1.158
		P_{min}	0.025	0.020	0.029	0.026	0.150	0.138	0.290	0.158
10	0.6769		0.0413	0.0288	0.0462	0.0274	0.6899	1.0974	1.0215	1.1487
20	0.6769		0.0517	0.0441	0.0462	0.0423	0.9784	1.0925	0.7878	1.0969
30	0.6792		0.0260	0.0311	0.0292	0.0418	0.5539	0.9869	1.1184	1.0744
40	0.6849		0.0265	0.0407	0.0321	0.0649	0.9930	0.8881	1.0841	0.8221
50	0.6889		0.0296	0.0420	0.0370	0.0315	0.8962	1.1150	1.0489	0.7722
60	0.6923		0.0408	0.0328	0.0510	0.0399	0.9578	1.0426	0.9413	0.8573
70	*0.7438*		*0.0349*	*0.0318*	*0.0320*	*0.0304*	*1.0850*	*0.9429*	*0.5286*	*0.6773*
80	0.7186		0.0303	0.0272	0.0421	0.0603	0.8767	0.9918	0.6812	1.0578
90	0.7264		0.0323	0.0238	0.0339	0.0440	1.0263	0.9761	0.6431	1.0636
100	0.7325		0.0477	0.0249	0.0509	0.0344	0.7789	1.1043	0.8739	0.8416

Note(s): Table 4 was originally generated based on the actual results of optimization and analysis technique through the first author of this manuscript. It never adopted from anywhere

Table 4. Effect of Av changes in the particle size = 180 with the faulty condition

the manufacturing system has been identified, such as 74.38% in the faulty and 76.01% in an ideal state. Finally, the optimized maintenance parameters for the better decision-making process of the maintenance management system in SMEs are shown in Table 6 and Table 7.

Table 5.
Effect of Av changes in the particle size = 180 with the ideal condition

Ideal ($X = 0$) Parameters			Failure rate λ_A	λ_B	λ_C	λ_D	Repair rate μ_A	μ_B	μ_C	μ_D
NI	Av	P_{max}	0.065	0.040	0.069	0.066	1.150	1.138	1.290	1.158
		P_{min}	0.025	0.020	0.029	0.026	0.150	0.138	0.290	0.158
10	0.7172		0.0302	0.0578	0.0622	0.0290	0.9617	0.9028	1.1233	0.9169
20	0.7274		0.0533	0.0237	0.0392	0.0376	0.7603	0.5341	1.2093	0.6685
30	0.7274		0.0405	0.0548	0.0381	0.0272	0.9128	0.9683	0.8885	0.4397
40	0.7367		0.0283	0.0238	0.0625	0.0577	0.9373	1.0065	0.6010	1.0979
50	0.7369		0.0332	0.0244	0.0630	0.0280	0.7124	0.5321	1.2651	0.8455
60	0.7372		0.0252	0.0213	0.0517	0.0568	1.0136	1.0231	1.2318	1.0294
70	*0.7601*		*0.0426*	*0.0440*	*0.0371*	*0.0276*	*1.0869*	*0.9243*	*1.0959*	*0.8592*
80	0.7490		0.0275	0.0202	0.0359	0.0442	0.7094	0.4304	0.9413	0.9668
90	0.7552		0.0431	0.0274	0.0554	0.0485	1.0918	0.8480	1.0685	1.0773
100	0.7558		0.0387	0.0345	0.0360	0.0261	1.0635	0.9194	0.9942	0.8817

Note(s): Table 5 was originally generated based on the actual results of optimization and analysis technique through the first author of this manuscript. It never adopted from anywhere

Table 6.
Optimal maintenance parameters with particle size = 180

Maintenance parameters	Machine A	Machine B	Machine C	Machine D	Machine AB	Machine CD	AV %	X
Failure rate (λ)	0.0498	0.0254	0.0448	0.0493	0.0509	0.0346	73	1
Repair rate (μ)	0.8102	0.7942	1.0108	1.0939	0.8139	0.8714		
Transition rate (ϕ)	0.0373	0.0023	0.0131	0.0166	0.0257	0.0114		
PM rate (η)	0.9435	0.9935	0.9720	0.8398	0.2410	0.4297		
Failure rate (λ)	0.0319	0.0252	0.0502	0.0403	0.0240	0.0497	77	0
Repair rate (μ)	0.7280	1.0348	0.9902	1.0470	0.8032	0.9722		
Transition rate (ϕ)	0.0313	0.0302	0.0282	0.0283	0.0217	0.0394		
PM rate (η)	1.0912	0.5993	0.8185	0.8584	0.3378	1.2004		

Note(s): Table 6 was originally generated based on the result of optimization technique by first author of this manuscript. It never adopted from anywhere

Table 7.
Optimal maintenance parameters with number of iteration = 70

Maintenance parameters	Machine A	Machine B	Machine C	Machine D	Machine AB	Machine CD	AV %	X
Failure rate (λ)	0.0349	0.0318	0.0320	0.0304	0.0550	0.0363	74	1
Repair rate (μ)	1.0850	0.9429	0.5286	0.6773	0.8570	1.0142		
Transition rate (ϕ)	0.0122	0.0014	0.0293	0.0086	0.0207	0.0187		
PM rate (η)	0.9767	0.1827	0.9554	0.7244	0.9207	0.9872		
Failure rate (λ)	0.0426	0.0440	0.0371	0.0276	0.0447	0.0270	76	0
Repair rate (μ)	1.0869	0.9243	1.0959	0.8592	0.8501	1.1736		
Transition rate (ϕ)	0.0124	0.0381	0.0122	0.0336	0.0222	0.0172		
PM rate (η)	0.6334	1.0042	1.2116	0.8613	0.7671	0.4874		

Note(s): Table 7 was originally generated based on the result of optimization analysis by first author of this manuscript. It never adopted from anywhere

6.1 Decision-making inferences

Every small and medium-sized manufacturing company wishes to install an appropriate and optimal decision-support system to improve maintenance and service management. As a result, the proposed research result aids maintenance managers in determining the appropriate range of maintenance parameters for individual production equipment. Based on these optimal maintenance parameters, optimal maintenance activities were organized appropriate in the manufacturing industry. The proposed minimum investment, machine downtime and maximum production can be achieved through the optimal maintenance management system.

(1) The industry's effective maintenance program aids in predicting the RUL of production machines and their essential components;

(2) To increase the efficiency of the maintenance team in the industry, they can also identify the impact of available changes in the repair and malfunction rate of production machinery and

(3) This RAM analysis result helps the manufacturing industry's maintenance department build the best preventive maintenance planning and scheduling activity.

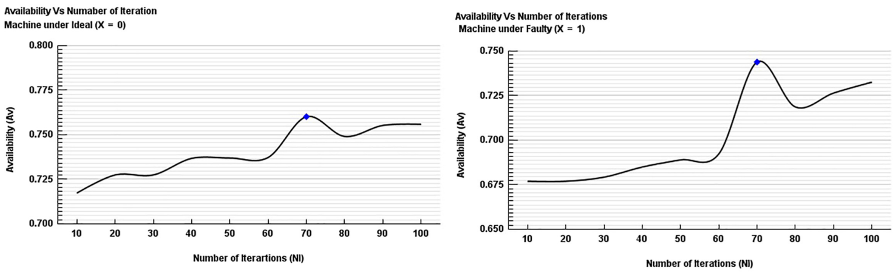
For instance, the critical part production unit in the electronic switch and sensor manufacturing industry was immediately employed in this optimization research investigation (industrial case study). It can be used in any manufacturing facility, independent of the order in which the processes are completed. There are some constraints to organizing the industry in this proposed optimal planning and scheduling framework of the maintenance management system. (1) Only examine the defined transition model of the machine's failures based on the past maintenance record in this optimization research investigation. (2) The creation of availability analysis mathematical equations is complicated by many concurrent machine failures. (3) The small and medium-scale manufacturing industry needs well-trained, skilled staff and data from the previous year's maintenance records to adopt the best decision-making process.

6.2 Managerial implication

The given manufacturing plant in the industry faces some managerial implications and benefits based on this proposed optimization solution of the maintenance management decision-making process. There are some most critical significant managerial implications of this proposed research analysis have been described below.

(1) The proposed optimal decision-making process of the maintenance management system identifies unscheduled machine breakdown time and minimizes the industry's unplanned maintenance manpower.

(2) The industry will develop defined maintenance financial statements and inventory management procedures based on these research findings (optimal decision-making process) to avoid unanticipated investment in service and maintenance actions;



Note(s): Figure 6 was genuinely prepared based on the analysis result through the first author of this manuscript, It never adopted from anywhere

Figure 6.
The effect of Av and iteration number changes in faulty and ideal conditions

(3) Implementing the most efficient workforce in the maintenance process, starting with the planning and scheduling of this industry's best decision-making maintenance management. This industry-defined recommended preventative maintenance program improved machine performance, productivity and customer satisfaction;

(4) The traditional preventive maintenance management system has been converted into a smart and autonomous through the application of this proposed optimal maintenance management scheduling framework;

(5) Through this prediction of the optimal maintenance parameters of the critical machine in the manufacturing plant the defined and optimized preventive maintenance planning and scheduling have been organized;

(6) The priority and hierarchy of the machine allocation of the preventive maintenance scheduling process will be updated and converted into the smart allocation based on the availability of the manufacturing system;

(7) The maintenance workforce allocation and the preventive maintenance scheduling have been autonomous through this proposed smart hierarchy approach in the industry and

(8) The maximum productivity of the manufacturing plant has been achieved through this proposed research analysis outcomes.

7. Conclusion

The availability, reliability analysis and optimal maintenance management system (complex machine components) of SMEs' critical part production plant in the southern region of Tamil Nadu, India, were established and shown in this research analysis using a PSO-based method. Based on this study, it is possible to improve the availability of machines and their complicated subcomponents by considerably enhancing the maintenance management system in SMEs. With the improved maintenance parameters of the machine, the RAM analysis of the critical part manufacturing system with PSO illustrates the availability differences in both faulty and excellent conditions. In a faulty state, the availability of SME manufacturing systems will increase by 74.38%, while availability in ideal conditions will increase by 77.93%. This proposed new model optimal maintenance management system framework would benefit maintenance and service department engineers (workers) in the SME industry by maximizing the performance and efficiency of the manufacturing plant. Unexpected machine downtime, production delays and the workforce of maintenance in SMEs are all decreased as a result of this proposed optimal decision-making procedure in maintenance management systems.

This research analysis could be used in the future to assess fluctuations in the availability of components for critical machinery in the manufacturing plant. We used the non-traditional method widely used in initial processing (PSO). This is followed by better results in conjunction with the nature-inspired algorithm (NIA) and the hybrid GA-PSO algorithm. It can be used in conjunction with PdM management systems in the manufacturing sector. These optimal maintenance parameters will be fed into the sensors to introduce autonomous preventive maintenance planning and smart maintenance practices that ensure an optimal decision-making process.

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