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Optimal Decision-Making Process for Maintenance and Service Management System in the Manufacturing Industry

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ABSTRACT

This real-time case study research employs a non-traditional optimization technique to enhance maintenance operations in small and medium enterprises (SMEs) to minimize investment costs. The study improves machine maintenance parameters through the application of a Genetic Algorithm (GA) to determine optimal solutions, thereby facilitating an effective decision-making framework for maintenance and service operations. Furthermore, the research analyzes variations in machine availability under both faulty and ideal operating conditions in SMEs using the Markov Decision Model. Mathematical formulations are developed based on the transition state diagrams of individual subsystems within the manufacturing plant, utilizing first-order differential equations. The primary objective of this research is to identify critical subsystems within the manufacturing plant and implement an optimal maintenance management system through a structured decision-making approach. The results obtained from the proposed algorithm indicate that machine availability in SMEs can be increased to 73.25% under faulty conditions, while system availability can reach 76.17% under ideal operating conditions. Based on these findings, a novel optimal decision support system is proposed for preventive maintenance management in SMEs, aiming to achieve maximum productivity with minimal maintenance and service investment through optimized planning and scheduling processes.

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1. Introduction

In this growing, competitive world, SMEs are increasingly interested in upgrading their current manufacturing industry to a computerized and smart industry, with key aspects such as meeting customer demand, increasing customer satisfaction, and increasing 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 a better decision-making process of optimal maintenance and service operations in the SMEs. The failure rate and repair rate of individual machines are measured by performing 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 behaviour of the machines.

The maintenance management system is the most complex function in the manufacturing industry compared to other activities because these functions directly affect the profit, smooth production running, and plant productivity,

etc. Over the last decade, the maintenance management system considered the major factors to achieving the best customer satisfaction in the competitive production world. In general, maintenance can be classified into three conditions (design out, scheduled, and breakdown). In this research, only the Age-Based Maintenance (ABM) activity is considered as the sub-classification of the scheduled maintenance (Preventive Maintenance) functions of the SMEs manufacturing industry. The sudden failure of the complex components in the machine will lead to a decrease in efficiency of the machine and unwanted production loss for the SMEs 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 components in the production plant of the industry. The main 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 machine. RQ1: Which are the most optimal maintenance parameters of the manufacturing machine to achieve the maximum availability?

1.1 Novelty of Proposed Optimal Maintenance Support System

The key novelty of this study is the incorporation of simultaneous machine failure states within the Markov Decision Process (MDP) framework, unlike conventional models that consider only independent single-machine failures. The proposed stochastic model integrates both individual and concurrent failure combinations into the transition state formulation, thereby improving the accuracy of prediction in complex SME manufacturing environments.

In addition, the optimized maintenance parameters $(\lambda, \mu, \eta, \phi)$ obtained through the Genetic Algorithm are designed for direct integration with real-time IIoT-based continuous monitoring systems. Thus, the study moves beyond theoretical optimization and establishes a closed-loop, data-driven smart maintenance framework that supports predictive maintenance, Remaining Useful Life (RUL) estimation, and adaptive preventive maintenance scheduling.

Therefore, this work extends beyond a purely empirical or simulation-based optimization study. It establishes a closed-loop smart maintenance framework, consisting of:

1. Stochastic modeling via MDP with simultaneous failure representation
2. Evolutionary optimization using GA
3. Real-time parameter deployment through sensor-driven monitoring
4. Decision-support integration for preventive maintenance scheduling

This integrated approach transforms the maintenance management system from a static schedule-based practice to a data-driven, predictive, and adaptive decision-support framework, specifically tailored for complex multi-machine manufacturing environments in SMEs.

2. Literature Review

The literature review is initially expanded by incorporating recently published studies related to manufacturing system advancements and preventive maintenance improvements in the manufacturing industry. Since the present study focuses on maintenance optimization, relevant research concerning production scheduling and preventive maintenance planning is examined, particularly in relation to the degradation behavior of critical mechanical components. The review begins by systematically presenting the key research contributions and methodologies adopted in this domain.

Ao et al. (2019) developed an integrated decision-making framework for semiconductor production scheduling and maintenance planning using the Markov Decision Process (MDP). The proposed model was implemented using MATLAB and EM-Plant simulation software to demonstrate optimal maintenance scheduling and planning strategies in industrial environments. Braga and Andrade (2019) investigated maintenance management issues associated with railway wheel set systems using Markov analysis. Their study focused on improving maintenance decision strategies, particularly component removal actions, compared to conventional maintenance practices. The research also provided an analytical approach to estimate the damage occurrence rate of critical railway components, including rail wheels and bearings. Celen and Djurdjanovic (2020) proposed an optimal decision-making framework for Flexible Manufacturing Systems (FMS) by addressing the coordination between production and maintenance operations. The study utilized Partially Observable Markov Decision Processes (POMDP) to develop an advanced maintenance modeling framework applicable to semiconductor manufacturing industries.

Dandotiya et al. (2008) addressed optimal maintenance scheduling challenges associated with Line Replaceable Units (LRUs) in aircraft fleet systems. The study proposed a strategic decision-making framework aimed at improving maintenance and service management efficiency within aircraft fleet operations. Han et al. (2022) focused on enhancing the accuracy and operational efficiency of road maintenance systems in China. The study implemented an Improved Weighted Random Forest (IWRF) algorithm integrated with Communication Weight Analysis (CA) and

the Analytic Hierarchy Process (AHP). The proposed approach minimized decision-making errors while incorporating human performance factors into the maintenance planning process. Havinga and de Jonge (Havinga & de Jonge, 2020) investigated condition-based maintenance management within the cyclic patrolling repairman problem using the Markov Decision Process (MDP). The study evaluated system performance under a control limit policy and developed an optimized maintenance cost function to improve maintenance decision strategies.

Similarly, Jin et al. (2020) developed an optimal maintenance strategy for complex multi-state degradation systems using the Semi-Markov Decision Process (SMDP) integrated with simulation techniques. The proposed framework enabled effective maintenance decision-making by capturing stochastic degradation behavior and identifying optimal maintenance actions under varying system states. Kamel et al. (2020) formulated a multi-level integrated mathematical model for preventive maintenance planning and scheduling in a sodium chloride manufacturing plant. The study employed a Genetic Algorithm (GA) implemented in MATLAB to determine optimal maintenance schedules. The proposed model minimized overall operational costs, including failure, repair, replacement, and unplanned downtime costs. Lee and Pan (2020) presented a Predictive Maintenance (PdM) framework for machine equipment by estimating the Remaining Useful Life (RUL) of machine tools using a Discrete-Time Markov Chain (DTMC). Additionally, system reliability and availability were evaluated using Bayesian Network (BN) modeling to enhance maintenance decision accuracy. Liang et al. (2020) investigated condition-based maintenance strategies for long-life infrastructure assets, specifically focusing on concrete bridge maintenance under environmental risk factors. The study applied a Continuous-Time Semi-Markov Chain (CTSMC) model to evaluate asset deterioration and develop an optimal maintenance cost strategy.

Mishra et al. (2020) investigated three maintenance models incorporating an opportunistic maintenance approach for series-connected multi-unit manufacturing systems. The study implemented a Java-based algorithm to evaluate maintenance strategies and improve system reliability and operational efficiency. Mathiyazhagan et al. (2019) provided a comprehensive review of existing research addressing the challenges associated with implementing green manufacturing concepts in sustainable industrial systems. The study critically analyzed environmental, economic, and operational constraints influencing sustainable manufacturing practices. Miwa and Oyama (2004) developed an optimal maintenance scheduling model for railway track systems using integer linear programming techniques. The proposed model aimed to improve maintenance planning efficiency by minimizing operational irregularities and enhancing track maintenance performance. Öztürk (2019) examined the optimal inventory control problem in manufacturing systems under stochastic supply chain conditions. The study addressed machine breakdown uncertainties and quality inspection requirements to develop an efficient inventory management strategy. Qiang et al. (2020) analyzed the optimal vehicle routing problem for gold chain logistics distribution using a greedy search algorithm. The proposed model focused on minimizing transportation routes and improving distribution efficiency.

Reddy et al. (2020) proposed a diagnostic framework for early detection of heart disease using an Adaptive Genetic Algorithm integrated with Fuzzy Logic (AGAFL). The developed model enhanced disease prediction accuracy, enabling early-stage diagnosis while reducing treatment costs and mortality risks. Srivastava et al. (2020) examined maintenance management challenges in sugar manufacturing plants by analyzing existing maintenance planning strategies. The study applied three Multi-Criteria Decision-Making (MCDM) approaches to develop an optimal maintenance scheduling and planning framework for improving plant operational efficiency. Sanusi et al. (2020) conducted a performance evaluation of series and parallel manufacturing systems by analyzing system availability based on key maintenance parameters, including failure rate and repair rate. The study utilized a Markov modeling approach combined with first-order differential equations to obtain optimal performance measures for manufacturing systems. Sharma and Vishwakarma (2014) analyzed the operational performance of sugar manufacturing industries using the Markov Decision Process (MDP). The research proposed an optimal maintenance policy and identified critical repairable subsystems within the manufacturing plant to enhance system reliability and availability. Sun et al. (2020) developed both manual and automated design algorithms for Convolutional Neural Network (CNN) architectures applied to industrial image classification problems. The study incorporated Genetic Algorithm (GA) techniques to optimize CNN architecture design and improve classification accuracy and computational efficiency.

Tewari and Malik (2016) presented a comprehensive review of availability analysis methodologies for thermal power plants by examining multiple research studies and real-time industrial case analyses. The study primarily utilized Markov modeling techniques to evaluate system availability and reliability in power generation systems. Vikrant and Atul (2016) analyzed availability variations in the paper manufacturing industry using Markov modeling integrated with Genetic Algorithm (GA) optimization techniques. The proposed approach enabled the identification of optimal maintenance parameters to enhance overall system availability in paper production processes. Velmurugan et al. (2022) investigated the performance evaluation of tyre manufacturing industries to support optimal maintenance decision-making processes. The study proposed a smart maintenance management framework using Machine Learning algorithms and hybrid Multi-Criteria Decision-Making (MCDM) techniques. The factor analysis conducted in the study facilitated the development of effective preventive maintenance strategies for improving manufacturing

system performance. Zhou et al. (2020) investigated the prediction of the Remaining Useful Life (RUL) of supercapacitors used in electric vehicle motor systems. Di Bona et al. investigated the AHP method, applied to safety and maintenance strategies. The study employed a hybrid approach combining Genetic Algorithm (GA) optimization with Recurrent Neural Network (RNN) modeling to accurately estimate supercapacitor degradation behavior. The proposed methodology improved product availability, reliability, and performance validation through accurate RUL prediction. Based on the review of the aforementioned studies, it is observed that Markov Decision Process (MDP)-based analytical techniques have been extensively applied to develop optimal maintenance management frameworks for small and medium-scale manufacturing industries. These approaches are predominantly focused on maintenance optimization under single-machine failure constraints within manufacturing systems. However, existing literature indicates a research gap, as limited studies have addressed simultaneous multiple machine failure scenarios in manufacturing plants (Bona et al., 2018; Di Bona et al., 2016).

The literature review highlights extensive research on maintenance optimization and reliability improvement using techniques such as MDP, GA, Machine Learning, and MCDM across various industrial applications. These studies significantly enhance maintenance planning, availability, and operational efficiency. However, most research primarily addresses single-machine failure conditions with limited consideration of subsystem interdependence. The impact of simultaneous multi-machine failures and integrated decision-support frameworks in SMEs remains insufficiently explored. Therefore, the present study aims to address these research gaps by formulating the following problem descriptions.

3. Problem Description

Small and medium-scale manufacturing industries (SMEs) encounter significant challenges in achieving optimal productivity, customer satisfaction, and efficient preventive maintenance planning and scheduling. The present research investigates real-time maintenance management issues in an SME located in the southern region of Tamil Nadu, India. The manufacturing plant experiences increased production delays, excessive machine downtime, and deterioration in product quality, primarily due to unplanned maintenance activities and inadequate workforce coordination within the maintenance team. This study focuses on evaluating existing maintenance practices using historical maintenance records and daily production data collected from the selected SME.

The objective is to develop an optimized decision-making framework for effective service planning and preventive maintenance scheduling. The major contributions of this study include: (a) analyzing maintenance management challenges through a real-time industrial case study, (b) identifying critical subsystems of the manufacturing plant based on availability variation using the Markov Decision Model, and (c) predicting optimal maintenance parameters, including failure and repair rates, using the Genetic Algorithm to support maintenance decision-making. The primary objective of this research is to develop and implement an optimal decision-support system that minimizes maintenance investment costs and machine downtime while maximizing maintenance workforce effectiveness and production productivity. The manufacturing workflow of the cross-member component production system is described in the following sections.

3.1 Case Study

This real-time case study research focuses on a small and medium-scale sheet metal forming industry, Sun Pressing Private Limited, located in the southern region of Tamil Nadu, India. The company manufactures various automobile components, including control arms, body panels, cross-members, and engine mounting parts. The present investigation specifically targets the production system associated with automobile cross-member components. Although the analysis is conducted based on a real-time industrial case study within this specific manufacturing facility, the developed methodology applies to a wide range of manufacturing industries with similar production characteristics. The cross-member component manufacturing process involves multiple sequential forming operations, including blanking, cropping, piercing, bending, embossing, powder coating, final inspection, and packaging. These sheet metal forming processes are performed using hydraulic and pneumatic press machines with capacities ranging from 100 tons to 500 tons. The operations are supported by dedicated tooling systems, including specialized dies and forming tools, installed across the shop floor production line. The detailed manufacturing workflow of the cross-member component production process is illustrated in Fig. 1.

3.2 Manufacturing System Description

(1) Raw Material: The manufacturing of automobile cross-member components utilizes stainless steel sheets with a nominal thickness of 8 mm, with dimensions specified according to product design requirements.

(2) Shearing or Blanking: The stainless-steel metal sheets are cut into predetermined dimensions as per required design specifications using a semi-automatic hydraulic shearing/blanking machine with capacity of 250-ton (Machine

S).

(3) Cropping: The sheared sheets undergo profile shaping to achieve through the required outline geometry of the pressing die. This operation is performed using a pedal-operated hydraulic pressing machine with capacity of 150 tons (Machine C).

(4) Piercing: After cropping, the workpiece is subjected to hole-making operations to produce holes of specified diameters (6 mm and 8 mm). This process is carried out using a 200-ton hydraulic pressing machine (Machine P) to achieve dimensional accuracy.

(5) Bending: Upon completion of the piercing operation, the component undergoes profile forming through a bending process using an automatically controlled 250-ton hydraulic pressing machine (Machine B) to obtain the required structural geometry.

(6) Embossing: In this stage, product identification and marking features such as company logos, part numbers, and positional symbols are embossed using a 150-ton pneumatic pressing machine in accordance with product design requirements.

(7) Powder Coating: The component undergoes manual assembly operations such as welding, riveting, and drilling, where required. The finished products are subsequently subjected to surface cleaning and powder coating processes to enhance corrosion resistance and surface finish.

(8) Final Inspection and Packaging: The finished products are subjected to final quality inspection to ensure compliance with dimensional and functional specifications. After meeting quality standards, the components are packaged and prepared for delivery to specific customers.

In the cross-member component manufacturing system, four primary machines, namely Shearing (S), Cropping (C), Piercing (P), and Bending (B), are actively involved in the production process. The service and maintenance strategies of these machines are governed by key maintenance parameters, including failure rate (λ), repair rate (μ), inspection rate (ϕ), and maintenance efficiency rate (η), which are associated with individual machine components. The primary maintenance objective is to optimize system availability and reliability of the cross-member production line by predicting and achieving maximum operational availability of the manufacturing system. Enhanced system availability directly contributes to improved production efficiency, customer satisfaction, and overall profitability in SMEs. The availability and reliability performance evaluation of the cross-member production system is presented in the subsequent sections. Initially, the notations and assumptions used for developing the availability model of the cross-member manufacturing system are defined and discussed.

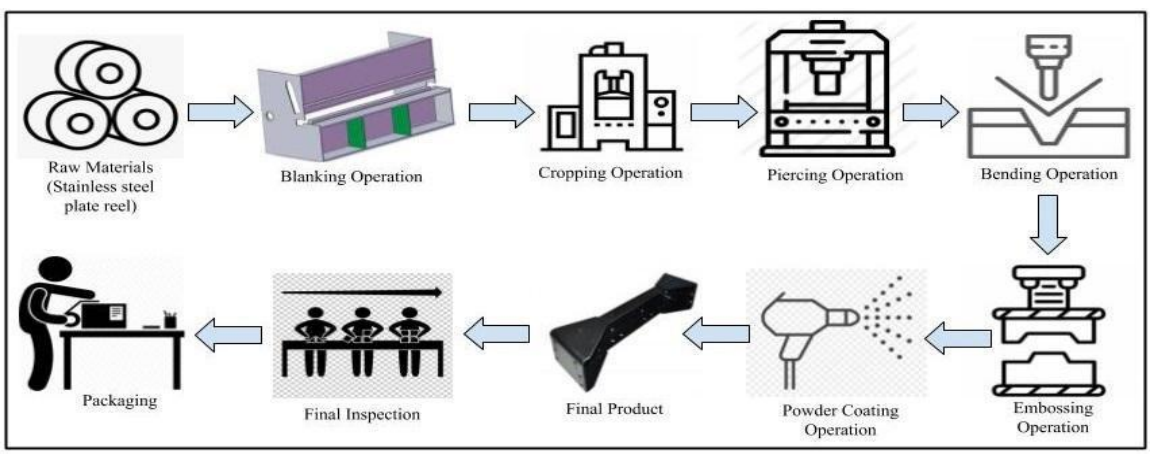

Figure 1: Manufacturing Flow Process of the Cross-Member Part Production

4. Mathematical Modelling of System Availability

The availability (Av) of the cross-member component production system in the small and medium-scale sheet metal forming industry is evaluated using the Markov Decision Process (MDP). The MDP-based framework is adopted to predict the stochastic behavior and performance variation of complex machine components based on key maintenance parameters, namely failure rate and repair rate, associated with individual machines within the manufacturing system. The modeling approach facilitates the evaluation of long-term system availability and supports optimal maintenance decision-making for SMEs. In the proposed MDP framework, availability prediction equations are formulated using the Transition State Diagram (TSD) representing the operational behavior of the manufacturing

system. The TSD models the probabilistic transitions between different operational states of each machine in the production line. Each manufacturing machine is assumed to operate under three distinct state conditions: (i) the original or fully operational state, denoted as state 0, (ii) the under-maintenance state, represented by odd-numbered states (1, 3, 5, …), and (iii) the failed state, represented by even-numbered states (2, 4, 6, …). This multi-state representation allows accurate modeling of maintenance and failure dynamics of the system

Initially, Machine S starts transition from the original operational state to the under-maintenance state. During that condition corrective maintenance operation is completed with minimal downtime, After repair completion, the machine is considered fully functional and equivalent to a new or restored operational state. The transition relationships among these operational states are represented using state transition probabilities and corresponding differential equations derived from the TSD. The sample transition state flow diagram representing the operational states of an individual machine is illustrated in Fig. 2.

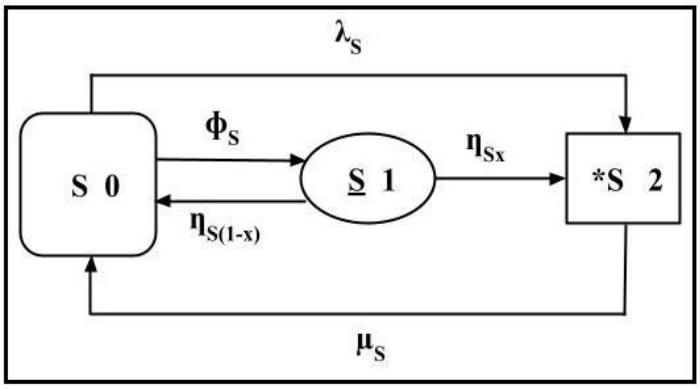

Figure 2: Sample Individual Transition State Flow

The Transition State Diagram (TSD) representing the cross-member production system under simultaneous machine failure conditions is illustrated in Fig. 3. The system availability and state transition behavior are mathematically modeled using the Markov Decision Process (MDP) framework. The governing equations describing system state transitions are formulated using first-order differential equations derived from the TSD representation. The mathematical formulation incorporates both individual machine failure states and simultaneous multi-machine failure conditions. The detailed derivation of these state transition equations is presented in the following section.

4.1 Notations

The notations employed in this optimization-based maintenance management analysis for the cross-member component production system are defined as follows:

S	Shearing or Blanking Machine.
C	Cropping Machine.
P	Piercing Machine.
B	Bending Machine.
S, C, P, B	Good state of the machines.
s, c, p, b	Under repair state of the machines.
*s,*c,*p,*b	Failed state of the machines.
λM	Rate of failure. (M = S, C, P, B, S&C, and P&B)
μM	Rate of repair.
ϕM	Rate of transition.
ηM	Rate of Preventive Maintenance.
x	Constant (0 for ideal and 1 for faulty)
P0 (t)	Probability functions of all machines are in good condition.
Pi(t)	Probability functions of the respective machines are in the under-repair state.
Pj(t)	Probability functions of the respective machines are in the failed state

4.2 Assumption

The availability analysis of the cross-member component production maintenance model in this study is based on the following assumptions:

o Initially, all production machines—Shearing (S), Cropping (C), Piercing (P), and Bending (B)—are assumed to be in a fully operational condition.

o The failure rate and repair rate of each production machine are considered constant and statistically independent, i.e., (λ_m, μ_m = Constant), where M = S, C, P, and B.

o Each repaired production machine is assumed to be restored to an "as good as new" operational condition.

o A dedicated maintenance team is assumed to be responsible for carrying out all maintenance and service operations of the production system.

o Each production machine is modeled with three operational states: operational (good) state, under-maintenance (repair) state, and failed state (e.g., S, s, and *s).

o Simultaneous failure conditions between production machines are considered in the model, particularly for machine combinations such as S & C and P & B.

o The preventive maintenance rate and state transition rate of each production machine are assumed to be constant, i.e., (η_m, ϕ_m = Constant)

4.3 Formulation of the Availability Prediction of the Manufacturing System

The state probability function of the machines in the cross-member production system initially represents the transition from the fully operational (good) state to the under-maintenance (repair) state. The system state transition behavior is mathematically modeled using the Markov Decision Process (MDP) framework. The corresponding state probability differential equation representing this transition is formulated as follows:

$$\eta_{\mathrm{m}}\, P_{\mathrm{i}}(t) \;=\; \varphi_{\mathrm{m}}\, P_0(t) \tag{1}$$

The state probability function of the machines in the cross-member production system represents the transition from the under-maintenance (repair) state to the failed state due to incomplete restoration or further component degradation. Following corrective maintenance and servicing operations, the failed machines are restored to a fully operational (good) state. The mathematical representation of these state transitions within the Markov Decision Process (MDP) framework is described as follows:

$$\mu_{\mathrm{m}}\, P_{\mathrm{j}}(t) \;=\; \eta_{\mathrm{m}} x P_{\mathrm{i}}(t) \;+\; \lambda_{\mathrm{m}}\, P_0(t) \tag{2}$$

4.4 4.4 Steady State Probability Condition of the Cross-Member Part Production Model

The cross-member component manufacturing system, comprising Machines S, C, P, and B, is analyzed under steady-state operating conditions. Under this assumption, the system transition behavior is considered time-invariant, and the time-dependent variations in state probabilities are assumed to be negligible, i.e., $\frac{dP(t)}{dt} = 0$or $t \to \infty$. By applying steady-state conditions to the availability (Av) differential equations (1–2), the corresponding steady-state probability equations for the cross-member production system are derived and presented as follows:

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

$$\eta_M P_i = \phi_M P_0 \tag{3}$$

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

The above equations (25-36) are solved recursively, and we get,

$$P_i = D_i P_0 P_j = D_j P_0 \tag{5}$$

Where

i = 1, 3, 5, 7, 9, and 11

j = 2, 4, 6, 8, 10, and 12

The steady-state probability equations of the cross-member component production system are established by applying the steady-state conditions to the availability (Av) equations (3–4). To obtain the complete probabilistic representation of the system states, a normalization condition is applied, which states that the sum of the probabilities of all possible system states is equal to unity. The corresponding normalization equation is formulated as follows:

Using Normalizing condition

$$\sum_{i=1}^{11} P_i \sum_{j=2}^{12} P_j = 1 \tag{6}$$

$$AV = \left[1 + \sum_{\mathrm{i}=1}^{11} \mathrm{P_i} + \sum_{\mathrm{j}=2}^{12} \mathrm{P_j}\right]^{-1} \tag{7}$$

$$A_v = P_0 \tag{8}$$

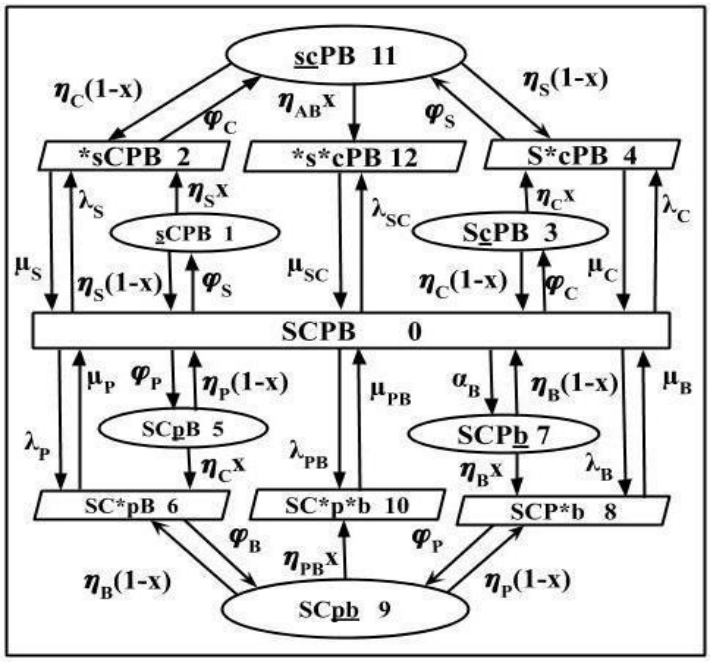

Figure 3: TSD of the Cross-Member Part Production System

Table 1: Input Numerical Values (Maintenance Parameters) of a Cross-Member Production System

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

5. Prediction of Maximum Availability by Using Genetic Algorithm

In this real-time case study, a widely adopted Non-Traditional Optimization Technique (NTOT), namely the Genetic Algorithm (GA), is employed to determine the optimal solution for the maintenance management system of the selected SME manufacturing process. As shown in Fig. 4, the Genetic Algorithm is an evolutionary computational optimization technique that finds global optimal solutions for challenging engineering problems by imitating biological genetic evolution mechanisms, including selection, crossover, and mutation. To improve the manufacturing system's overall performance, the GA is used to optimize crucial maintenance metrics such system availability, failure rate, repair rate, and preventive maintenance rate.

The optimization procedure using GA is implemented through the following steps:

Step 1: Set up the GA control parameters and maintenance variables, such as the failure rate (λ), repair rate (μ), transition rate (ϕ), and preventive maintenance rate (η).

Step 2 & 3: Create a starting population at random and use chromosomal strings to encode the solution variables. Analyze each member of the original population's fitness function, which is represented by system availability (Av).

Step 4 & 5**:** Create a mating pool by choosing members of the current population according to their level of fitness. For reproduction, choose two parent chromosomes at random from the mating pool.

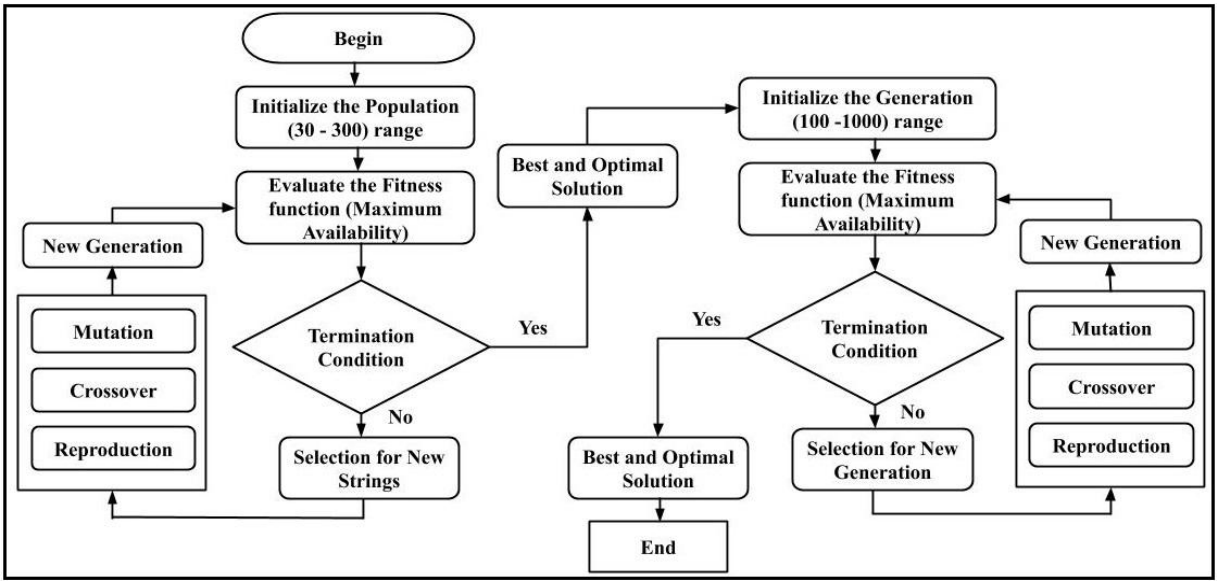

Figure 4: A typical framework for the Genetic Algorithm Technique

Step 6 & 7: To create offspring solutions, perform crossover operations on the chosen parent chromosomes. To preserve genetic diversity and prevent premature convergence, carry out mutation operations as needed.

Step 8 & 9: Include the recently produced offspring in the population of the following generation. Determine everyone's fitness function (Av) in the updated population.

Step 10 & 11: Determine which individuals of the previously and recently created populations are the most suitable. Iteratively repeat Steps 4 through 10 until the convergence requirements are met and the best solution that maximizes system performance is found.

5.1 GA Parameters

5.1.1 Solution Coding

The maintenance parameters, namely failure rate (λ), repair rate (μ), inspection rate (ϕ), and preventive maintenance rate (η), are encoded using a fixed-point integer representation scheme to facilitate computational implementation within the Genetic Algorithm framework. Each encoded maintenance parameter is mapped to a predefined permissible range. $[P_{Min}, P_{Max}]$, where $P_{Min}$and P_{Max}denote the lower and upper bounds of feasible maintenance parameter values for each subsystem of the production system. This encoding strategy ensures that the search space of the optimization algorithm is restricted to realistic and operationally valid parameter limits while maintaining numerical stability and solution accuracy during the evolutionary optimization process.

The fitness function is defined as:

$$\text{Maximize } F(\lambda,\mu,\eta,\phi) = Av(\lambda,\mu,\eta,\phi) \tag{9}$$

$$\lambda_{min} \le \lambda \le \lambda_{max}$$

$$\mu_{min} \le \mu \le \mu_{max}$$

$$\eta_{min} \le \eta \le \eta_{max}$$

$$\phi_{min} \le \phi \le \phi_{max}$$

$$\lambda>0,\ \mu>0,\ \eta>0,\ \phi>0$$

5.1.2 Population Size

The initial population of candidate solutions is generated randomly to initiate the Genetic Algorithm (GA) optimization process. The population size represents the total number of potential solutions included in each generation and is primarily determined based on the complexity and dimensionality of the optimization problem. The initial population is created only once at the beginning of the first generation and serves as the foundation for subsequent evolutionary operations such as selection, crossover, and mutation. The selection of an appropriate population size is a critical design parameter in GA implementation, as it directly influences convergence speed, solution diversity, and computational efficiency.

In the present study, four maintenance parameters—failure rate (λ), repair rate (μ), inspection rate (ϕ), and preventive maintenance rate (η)—are considered across six different operational state conditions, resulting in a total of 240 initial solution samples used for GA testing. The representative sample encoding structure of the solution variables is illustrated in Fig. 5. The proposed GA framework was experimentally evaluated using multiple population sizes ranging from 10 to 500 individuals. Based on convergence stability, solution consistency, and optimization performance, as demonstrated in Table 2, Table 3, and Fig. 10, an optimal population size of 270 individuals was selected for the final experimental analysis.

5.1.3 Selection Operator

The Simple Rank-Based Selection method is employed to generate a new population during each iteration of the Genetic Algorithm (GA) cycle. In this selection mechanism, individuals within the population are ordered based on their fitness function values, and selection probability is assigned according to their relative ranking rather than their absolute fitness magnitude. By preventing excessive reproduction of a small selection of highly fit individuals, this ranking technique avoids premature convergence, especially in situations where fitness variance within the population is relatively high. Furthermore, when the fitness variance is low, rank-based selection sustains steady selection pressure, guaranteeing balanced exploration and exploitation throughout the evolutionary optimization process. Regardless of the absolute fitness differences between individuals, the predicted selection probability ratio between two successive individuals, ranked as i and i+1, is constant. Each member of the population is given a rank in increasing order of fitness using this method, which ranges from 1 to N, where N is the population size. The expected selection probability of the i^{th}individual in the population at generation $t$is mathematically expressed as follows

Parameter	PRA										FRB										FRC									
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Sample	0	1	0	1	1	1	1	1	1	1	0	0	0	0	0	0	1	1	0	0	1	0	1	1	1	0	0	1	1	1
Obj. Value	0.0649										0.0275										0.0653									

FRD										FRAB										FRCD									
31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60
0	1	0	1	1	1	0	0	0	1	1	1	1	0	0	0	1	0	1	1	1	1	0	1	0	0	0	1	1	1
0.0483										0.0549										0.0626									

RRA										RRB										RRC									
61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90
1	1	1	1	1	0	1	0	0	0	0	1	0	1	0	1	1	0	0	0	0	0	0	0	1	1	0	0	0	1
0.2429										0.2417										0.8377									

RRD										RRAB										RRCD									
91	92	93	94	95	96	97	98	99	100	101	102	103	104	105	106	107	108	109	110	111	112	113	114	115	116	117	118	119	120
0	0	1	0	0	0	1	0	1	1	0	1	0	0	0	0	0	0	0	0	0	1	1	0	0	1	0	1	1	0
0.9756										0.146										0.6367									

TRA										TRB										TRC									
121	122	123	124	125	126	127	128	129	130	131	132	133	134	135	136	137	138	139	140	141	142	143	144	145	146	147	148	149	150
1	1	1	1	1	1	0	1	0	1	0	1	0	1	0	0	0	1	0	1	1	0	1	1	1	0	0	1	0	0
0.0346										0.0265										0.0112									

TRD										TRAB										TRCD									
151	152	153	154	155	156	157	158	159	160	161	162	163	164	165	166	167	168	169	170	171	172	173	174	175	176	177	178	179	180
1	1	1	0	1	1	0	0	0	1	0	0	0	0	1	1	1	0	1	1	1	1	1	1	0	1	0	0	1	1
0.0262										0.0425										0.0409									

PRA										PRB										PRC									
181	182	183	184	185	186	187	188	189	190	191	192	193	194	195	196	197	198	199	200	201	202	203	204	205	206	207	208	209	210
1	0	1	1	1	1	1	0	0	1	1	0	1	0	0	0	0	1	1	0	1	0	1	1	0	1	1	0	0	0
0.743										0.5504										0.4566									

PRD										PRAB										PRCD									
211	212	213	214	215	216	217	218	219	220	221	222	223	224	225	226	227	228	229	230	231	232	233	234	235	236	237	238	239	240
0	1	1	1	0	1	1	0	0	1	0	0	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	1	0	0
0.7283										1.1476										0.419									

Figure 5: Sample Parameters of GA

$$Expectedvalue(i,t) = (min) + (max - min) \times \frac{rank(i,t)-1}{N-1} \quad (10)$$

were

N = Population size
Min = 0.4
Max = 1.6

5.1.4 Cross-Over Operator

During the crossover operation, new offspring chromosomes are generated by exchanging genetic information between parent chromosomes selected from the mating pool. In the proposed optimization framework, a hierarchical chromosome representation is adopted, necessitating the use of both single-point crossover and its advanced variant, Partial Mapped Crossover (PMX). Initially, a crossover cut point is randomly selected along the length of the chromosome. The single-point crossover operator is applied to the first layer of the chromosome structure, while PMX is applied to the second layer to preserve gene sequence validity and prevent the generation of infeasible or illegal chromosome structures.

Crossover Starts	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Random no for CO: 0.20	1	0	1	1	1	0	0	1	1	1	0	0	0	1	0	0	0	1	0	1	1	1	1	1	1	1	1	0	1	0
Before Crossover	0	0	0	1	1	1	0	1	1	0	1	0	1	1	1	1	0	1	0	1	1	1	0	1	1	1	1	1	1	1

31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60
1	1	0	1	1	1	1	0	0	0	1	1	1	0	0	0	1	1	0	0	1	1	0	1	1	0	1	0	0	1
0	1	0	0	0	1	1	0	1	0	1	1	0	0	0	0	0	1	1	0	0	1	0	0	1	0	1	0	0	0

61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90
1	1	1	0	1	1	1	0	1	1	1	0	1	0	0	0	0	1	1	1	0	0	0	1	1	1	0	1	1	0
1	0	0	1	1	0	1	1	0	0	0	0	1	0	1	1	1	1	0	0	1	0	0	1	1	1	0	1	1	1

91	92	93	94	95	96	97	98	99	100	101	102	103	104	105	106	107	108	109	110	111	112	113	114	115	116	117	118	119	120
0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	1	0	1	0	0	0	0	1	1
0	0	0	0	1	0	1	0	0	1	0	1	0	1	1	1	1	0	0	1	0	1	0	1	1	1	0	1	0	1

121	122	123	124	125	126	127	128	129	130	131	132	133	134	135	136	137	138	139	140	141	142	143	144	145	146	147	148	149	150
0	1	0	1	0	0	0	1	1	1	1	1	0	0	1	0	0	1	1	1	0	1	0	1	0	1	1	1	1	0
1	1	0	0	0	1	1	0	0	1	0	0	1	1	0	0	0	0	0	1	1	0	0	1	1	1	0	0	1	0

151	152	153	154	155	156	157	158	159	160	161	162	163	164	165	166	167	168	169	170	171	172	173	174	175	176	177	178	179	180
1	0	0	0	1	1	1	1	0	1	1	0	1	0	1	1	1	0	1	0	0	0	1	1	0	0	0	0	0	0
1	1	1	0	0	1	1	0	0	0	0	1	1	0	1	1	1	0	0	0	1	1	0	0	1	0	1	0	0	1

181	182	183	184	185	186	187	188	189	190	191	192	193	194	195	196	197	198	199	200	201	202	203	204	205	206	207	208	209	210
0	1	1	1	1	1	0	1	1	0	0	1	0	1	1	0	1	1	1	0	1	1	0	1	0	1	1	1	0	0
0	0	1	0	1	1	0	1	1	0	0	0	0	0	0	1	0	0	0	0	1	0	0	1	1	1	1	0	0	0

211	212	213	214	215	216	217	218	219	220	221	222	223	224	225	226	227	228	229	230	231	232	233	234	235	236	237	238	239	240
1	0	1	1	1	1	1	0	0	0	0	1	1	0	1	1	0	1	0	0	0	0	0	0	0	1	0	1	1	0
0	0	1	1	1	0	1	1	1	1	0	1	1	1	0	1	0	1	0	0	1	1	1	1	0	1	0	0	0	0

Figure 6: Before Cross-Over of the Sample

The proposed GA methodology employs a single-point crossover mechanism as the primary recombination operator. Experimental analysis was conducted by varying the crossover probability within the range of 0.3 to 0.9 to evaluate its influence on solution convergence and search efficiency. Based on optimization performance and solution stability, a crossover probability value of 0.8 was selected as the optimal parameter for the study. Illustrative examples of chromosome recombination using PMX before and after the crossover operation are presented in Fig. 6 and Fig. 7

CO site: 17	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
After Crossover	1	0	1	1	1	0	0	1	1	1	0	0	0	1	0	0	0	1	0	1	1	1	0	1	1	1	1	1	1	1
	0	0	0	1	1	1	0	1	1	0	1	0	1	1	1	1	0	1	0	1	1	1	1	1	1	1	1	0	1	0

31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60
0	1	0	0	0	1	1	0	1	0	1	1	0	0	0	0	0	1	1	0	0	1	0	0	1	0	1	0	0	0
1	1	0	1	1	1	1	0	0	0	1	1	1	0	0	0	1	1	0	0	1	1	0	1	1	0	1	0	0	1

61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90
1	0	0	1	1	0	1	1	0	0	0	0	1	0	1	1	1	1	0	0	1	0	0	1	1	1	0	1	1	1
1	1	1	0	1	1	1	0	1	1	1	0	1	0	0	0	0	1	1	1	0	0	0	1	1	1	0	1	1	0

91	92	93	94	95	96	97	98	99	100	101	102	103	104	105	106	107	108	109	110	111	112	113	114	115	116	117	118	119	120
0	0	0	0	1	0	1	0	0	1	0	1	0	1	1	1	1	0	0	1	0	1	0	1	1	1	0	1	0	1
0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	1	0	1	0	0	0	0	1	1

121	122	123	124	125	126	127	128	129	130	131	132	133	134	135	136	137	138	139	140	141	142	143	144	145	146	147	148	149	150
1	1	0	0	0	1	1	0	0	1	0	0	1	1	0	0	0	0	0	1	1	0	0	1	1	1	0	0	1	0
0	1	0	1	0	0	0	1	1	1	1	1	0	0	1	0	0	1	1	1	0	1	0	1	0	1	1	1	1	0

151	152	153	154	155	156	157	158	159	160	161	162	163	164	165	166	167	168	169	170	171	172	173	174	175	176	177	178	179	180
1	1	1	0	0	1	1	0	0	0	0	1	1	0	1	1	1	0	0	0	1	1	0	0	1	0	1	0	0	1
1	0	0	0	1	1	1	1	0	1	1	0	1	0	1	1	1	0	1	0	0	0	1	1	0	0	0	0	0	0

181	182	183	184	185	186	187	188	189	190	191	192	193	194	195	196	197	198	199	200	201	202	203	204	205	206	207	208	209	210
0	0	1	0	1	1	0	1	1	0	0	0	0	0	0	1	0	0	0	0	1	0	0	1	1	1	1	0	0	0
0	1	1	1	1	1	0	1	1	0	0	1	0	1	1	0	1	1	1	0	1	1	0	1	0	1	1	1	0	0

211	212	213	214	215	216	217	218	219	220	221	222	223	224	225	226	227	228	229	230	231	232	233	234	235	236	237	238	239	240
0	0	1	1	1	0	1	1	1	1	0	1	1	1	0	1	0	1	0	0	1	1	1	1	0	1	0	0	0	0
1	0	1	1	1	1	1	0	0	0	0	1	1	0	1	1	0	1	0	0	0	0	0	0	0	1	0	1	1	0

Figure 7: After the Crossover of the Sample

5.1.5 Mutation Operator

Mutation is incorporated into the Genetic Algorithm (GA) to prevent premature convergence and to enhance exploration of the global solution search space. Unlike the crossover operation, which recombines genetic information between parent chromosomes, mutation introduces random alterations in one or more genes within an individual chromosome. This process helps maintain genetic diversity within the population and improves the algorithm's capability to escape local optima.

In the proposed optimization framework, a conventional exchange mutation operator is employed, wherein selected gene positions within a chromosome are interchanged to generate new solution variants. Experimental evaluation of the GA was conducted using mutation probabilities ranging from 0.001 to 0.1 to assess its influence on convergence behavior and search diversity. Based on the observed optimization performance and stability, a mutation probability of 0.03 was identified as the most effective parameter for maintaining population diversity while ensuring efficient convergence. Illustrative examples demonstrating chromosome structures before and after the mutation operation are presented in Fig. 8 and Fig. 9.

Before Mutation	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Random no for CO: 0.298	1	0	1	1	1	0	0	1	1	1	0	0	0	1	0	0	0	1	0	1	1	1	1	1	1	1	1	0	1	0

31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60
1	1	0	1	1	1	1	0	0	0	1	1	1	0	0	0	1	1	0	0	1	1	0	1	1	0	1	0	0	1

91	92	93	94	95	96	97	98	99	100	101	102	103	104	105	106	107	108	109	110	111	112	113	114	115	116	117	118	119	120
0	0	0	1	0	0	0	0	0	0	0	1	0	1	0	1	1	1	0	0	0	0	1	0	0	0	0	1	1	0

121	122	123	124	125	126	127	128	129	130	131	132	133	134	135	136	137	138	139	140	141	142	143	144	145	146	147	148	149	150
1	1	0	0	0	0	0	0	0	0	1	0	0	1	1	0	0	1	0	0	1	0	1	0	0	1	1	1	0	1

151	152	153	154	155	156	157	158	159	160	161	162	163	164	165	166	167	168	169	170	171	172	173	174	175	176	177	178	179	180
1	1	1	1	0	0	0	0	0	1	1	0	1	1	1	0	1	1	0	1	0	1	0	1	1	1	0	1	1	0

181	182	183	184	185	186	187	188	189	190	191	192	193	194	195	196	197	198	199	200	201	202	203	204	205	206	207	208	209	210
1	1	1	0	0	0	0	0	0	0	1	0	1	1	0	1	1	0	0	1	1	0	1	0	1	0	1	1	1	1

211	212	213	214	215	216	217	218	219	220	221	222	223	224	225	226	227	228	229	230	231	232	233	234	235	236	237	238	239	240
1	0	0	0	0	1	0	1	1	1	1	1	0	0	1	0	0	0	1	1	1	1	1	1	0	1	1	1	1	1

Figure 8: Before the Mutation of the Sample.

After Mutation	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Mutation sites: 176, 75	1	0	1	1	1	0	0	1	1	1	0	0	0	1	0	0	0	1	0	1	1	1	1	1	1	1	1	0	1	0

31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60
1	1	0	1	1	1	1	0	0	0	1	1	1	0	0	0	1	1	0	0	1	1	0	1	1	0	1	0	0	1
61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90
1	1	1	0	1	1	1	0	1	1	1	0	1	0	1	0	0	1	1	1	0	0	0	1	1	1	0	1	1	0
91	92	93	94	95	96	97	98	99	100	101	102	103	104	105	106	107	108	109	110	111	112	113	114	115	116	117	118	119	120
0	0	0	1	0	0	0	0	0	0	0	1	0	1	0	1	1	1	0	0	0	0	1	0	0	0	0	1	1	0
121	122	123	124	125	126	127	128	129	130	131	132	133	134	135	136	137	138	139	140	141	142	143	144	145	146	147	148	149	150
1	1	0	0	0	0	0	0	0	0	1	0	0	1	1	0	0	1	0	0	1	0	1	0	0	1	1	1	0	1
151	152	153	154	155	156	157	158	159	160	161	162	163	164	165	166	167	168	169	170	171	172	173	174	175	176	177	178	179	180
1	1	1	1	0	0	0	0	0	1	1	0	1	1	1	0	1	1	0	1	0	1	0	1	1	0	0	1	1	0
181	182	183	184	185	186	187	188	189	190	191	192	193	194	195	196	197	198	199	200	201	202	203	204	205	206	207	208	209	210
1	1	1	0	0	0	0	0	0	0	1	0	1	1	0	1	1	0	0	1	1	0	1	0	1	0	1	1	1	1
211	212	213	214	215	216	217	218	219	220	221	222	223	224	225	226	227	228	229	230	231	232	233	234	235	236	237	238	239	240
1	0	0	0	0	1	0	1	1	1	1	1	0	0	1	0	0	0	1	1	1	1	1	1	0	1	1	1	1	1

Figure 9: After the Mutation of the Sample

5.1.6 Termination Criterion

Based on extensive experimental trials, the total number of Genetic Algorithm (GA) iterations was fixed at 1000 cycles, as this configuration consistently produced stable and satisfactory optimization results across different initial population datasets. The convergence characteristics and solution consistency corresponding to this iteration limit are demonstrated in Table 4, Table 5, and Fig. 10.

G max=1000

The proposed GA optimization framework was implemented under two distinct operational maintenance scenarios:

Case 1: Preventive maintenance is applied to all machines and subsystems within the production system. Under this condition, minor faults are addressed immediately through preventive maintenance actions, thereby preventing the occurrence of major failures and reducing the requirement for extensive corrective repair activities. For this operational condition, the decision parameter is defined as $b = 0$.

Case 2: Preventive maintenance is not implemented due to associated operational costs, and maintenance actions are performed only after failure occurrence. In this scenario, machines are allowed to operate until breakdown, leading to increased corrective maintenance requirements. For this operational condition, the decision parameter is defined as $b = 1$.

5.1.7 GA Parameter Selection

Extensive experimental runs across several parameter ranges were used to identify the ideal values of the Genetic Algorithm (GA) control parameters. The crossover probability ranged from 0.4 to 0.9, and it was shown that a crossover probability of 0.8 led to better optimization performance and faster convergence. Similarly, a mutation probability of 0.2 was shown to be the most effective number for conserving high-quality solutions while maintaining solution diversity during the evolutionary process. The mutation probability was examined in the range of 0.01 to 0.3. The following final GA control settings were chosen for the optimization analysis: The population is 270 with 1000 generations.

- Crossover probability = 0.8
- Mutation probability = 0.2

As illustrated in Fig. 10, the maximum availability (Av) of the manufacturing system was achieved at 69.80% under faulty operating conditions and 76.17% under ideal operating conditions. The corresponding optimal maintenance parameters, including failure rate (λ), repair rate (μ), inspection rate (ϕ), and preventive maintenance rate (η), obtained for the selected population and generation sizes are presented in Table 6 & Table 7. Furthermore, as shown in Fig. 11, the manufacturing system availability improved to 73.25% under faulty conditions and 75.58%

under ideal operating conditions. The corresponding optimized maintenance parameter values for these performance outcomes are also summarized in Table 6 & Table 7. The variation in availability (Av) of the cross-member component production system under faulty operating conditions was analyzed across a population size range of 30 to 300, and the corresponding results are presented in Table 2. The population sizes at which maximum system availability was achieved, along with the associated optimal maintenance parameters, specifically failure rate (λ) and repair rate (μ), are highlighted. Similarly, the availability variation of the production system under ideal operating conditions across the same population size range is presented in Table 3, where the optimal population sizes and corresponding maintenance parameters are identified.

The graphical representation of availability variations for both faulty and ideal operating conditions is illustrated in Fig. 10, where the horizontal axis represents the population size and the vertical axis denotes system availability. The results indicate that the availability of the manufacturing system exhibits a gradual increasing trend with respect to the variation and optimization of machine maintenance parameters, including failure rate (λ), repair rate (μ), inspection rate (ϕ), and preventive maintenance rate (η). Based on graphical and tabulated analysis, the maximum system availability was observed to be 69.80% under faulty operating conditions and 76.17% under ideal operating conditions. The corresponding optimized maintenance parameter values are summarized in Table 6 & Table 7. Furthermore, the obtained system availability and maintenance parameter optimization results were compared with previously published research findings (Sharma & Vishwakarma, 2014) to validate the effectiveness and reliability of the proposed optimization framework.

The optimal population size identified from the GA optimization process, consisting of 270 individuals, along with the corresponding maintenance parameters (failure rate (λ), repair rate (μ), inspection rate (ϕ), and preventive maintenance rate (η)), was further evaluated across different generation ranges varying from 100 to 1000. This analysis was conducted to examine the convergence behavior of the GA and to verify whether the selected population size provides reliable and stable optimization results suitable for maintenance planning in SMEs. The variation in system availability (Av) of the cross-member production system under faulty operating conditions across the generation range of 100 to 1000 is presented in Table 4. Similarly, the availability variation under ideal operating conditions across the same generation range is presented in Table 5. The comparative graphical representation of availability variations under both faulty and ideal operating conditions is illustrated in Fig. 11, where the horizontal axis represents the number of generations and the vertical axis represents the system availability.

The analysis indicates that system availability demonstrates a progressive improvement trend with an increase in generation count, reflecting enhanced optimization of maintenance parameters (λ, μ, ϕ, and η). The convergence pattern confirms that the GA effectively identifies near-global optimal maintenance solutions as the number of generations increases. Based on graphical interpretation, the maximum availability of the manufacturing system was achieved at 73.25% under faulty operating conditions and 75.58% under ideal operating conditions. The optimized maintenance parameter values corresponding to these availability levels provide improved decision-support capability for maintenance management in SMEs. The final optimized maintenance parameters derived from the GA optimization process are summarized in Table 6 & Table 7, which supports effective preventive maintenance planning, reduced machine downtime, and improved production system reliability.

5.2 Decision-Making Inferences

Small and medium-scale manufacturing industries require systematic and optimized decision-support frameworks to enhance maintenance and service management efficiency. In this research study, a real-time industrial case investigation was conducted at a sheet metal forming industry, Sun Pressing Private Limited, Madurai. Before the implementation of this analytical study, the organization followed a conventional preventive maintenance schedule based primarily on empirical assumptions without quantitative or mathematical validation. The present research identified the critical subsystems within the production line and determined their optimal maintenance parameters using a structured analytical and optimization framework. Based on the outcomes of this analysis, an optimized preventive maintenance schedule was developed to achieve maximum operational availability of the manufacturing systems. The results of this study provide maintenance managers with quantitative guidance for identifying the optimal maintenance parameter ranges specific to individual production machines.

By utilizing the optimized maintenance parameters derived from this research, industries can effectively plan and execute maintenance activities with improved precision. The implementation of the proposed optimal maintenance management framework facilitates a reduction in maintenance expenditure, minimization of machine downtime, and enhancement of overall production productivity and system reliability.

1. The proposed optimization framework facilitates the prediction of the Remaining Useful Life (RUL) of manufacturing machines and their critical components by establishing an optimized and data-driven

maintenance policy. This enables proactive maintenance interventions and reduces unexpected equipment failures.

2. The analysis systematically evaluates the influence of variations in system availability with respect to machine failure rates and repair rates. This relationship provides quantitative insights that assist in improving maintenance team efficiency, resource allocation, and response planning within the manufacturing environment.
3. The Reliability, Availability, and Maintainability (RAM) analysis outcomes support the development of optimized Preventive Maintenance (PM) planning and scheduling strategies. These strategies enhance maintenance decision-making processes and improve overall system reliability and operational continuity

The proposed optimization methodology was validated through its direct application to a cross-member part production unit in a sheet metal forming industry under an industrial case study. Although the framework is primarily developed for sequential manufacturing systems, it can be extended to other production plants with similar process configurations. However, the proposed optimal maintenance planning and scheduling framework possesses certain operational and methodological limitations:

a) The optimization model considers only predefined machine failure transition states derived from historical maintenance records, which may not fully capture dynamic or unforeseen failure behaviors.

b) The mathematical formulation of availability analysis becomes significantly complex when incorporating a large number of simultaneous machine failure conditions, thereby increasing computational complexity.

c) The practical implementation of the proposed optimization-based decision-support system in small and medium-scale manufacturing industries requires skilled maintenance personnel and the availability of comprehensive historical maintenance datasets for accurate predictive modeling and decision-making.

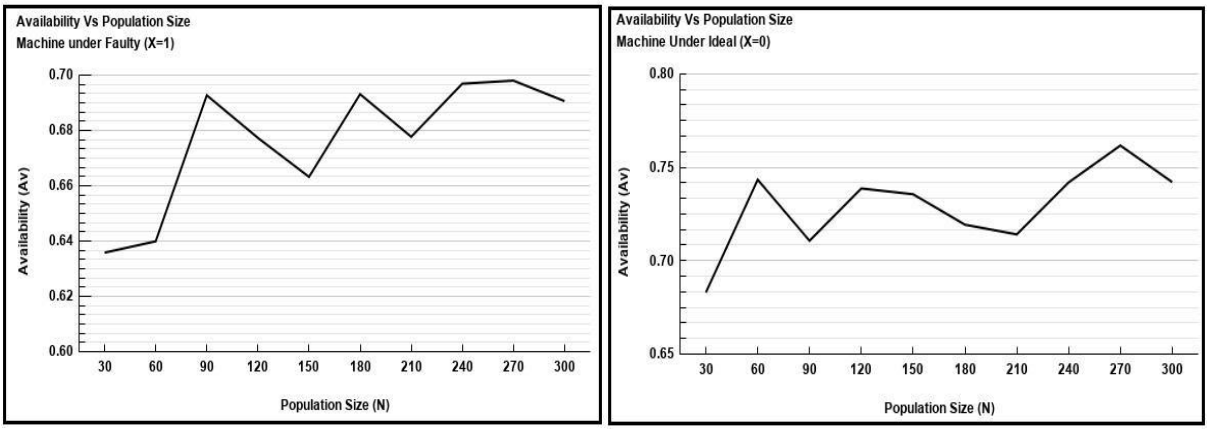

Figure 10: Effect of Av and Generation Variation in Faulty and Ideal Condition

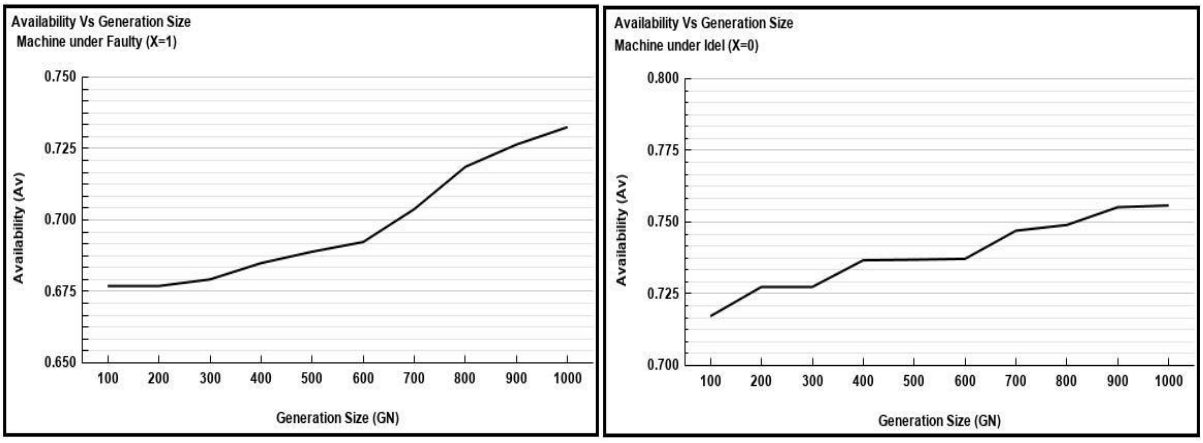

Figure 11: Effect of Av and Population Variation in Faulty and Ideal Conditions

Table 2: Effect of Av Changes in the Generation Size=100 with Faulty Condition

B=1		Failure Rate						Repair Rate						Transition Rate						Preventive Maintenance Rate					
Parameters		λ_S	λ_C	λ_P	λ_B	λ_{SC}	λ_{PB}	μ_S	μ_C	μ_P	μ_B	μ_{SC}	μ_{PB}	ϕ_S	ϕ_C	ϕ_P	ϕ_B	ϕ_{SC}	ϕ_{PB}	η_S	η_C	η_P	η_B	η_{SC}	η_{PB}
N	AV P_{max}	.065	.040	.069	.066	.062	.067	1.150	1.138	1.290	1.158	1.144	1.224	.047	.041	.045	.044	.048	.049	1.120	1.170	1.350	1.120	1.150	1.240
	AV P_{min}	.025	.020	.029	.026	.022	.027	.150	.138	.290	.158	.144	.224	.007	.001	.005	.004	.008	.009	.120	.170	.350	.120	.150	.240
30	0.6358	.047	.054	.046	.044	.033	.032	1.062	.924	.417	1.051	.696	.664	.038	.007	.006	.032	.029	.017	.852	.852	.514	.927	.912	.641
60	0.6399	.032	.042	.033	.049	.033	.058	.711	1.035	1.054	.960	.788	1.142	.028	.028	.030	.018	.047	.009	1.009	.600	.588	.447	.293	1.003
90	0.6927	.042	.036	.040	.030	.024	.049	.726	1.049	1.229	1.132	.741	.774	.032	.007	.008	.014	.008	.029	.476	.312	1.184	.974	.557	.289
120	0.6773	.035	.058	.042	.039	.026	.032	.512	.973	1.098	.735	1.096	.833	.019	.015	.014	.013	.029	.042	.457	.906	.512	1.118	.301	.727
150	0.6632	.061	.044	.047	.055	.023	.048	.999	.952	1.248	.723	.990	.899	.009	.038	.031	.014	.032	.012	.888	1.120	1.133	.558	.872	.909
180	0.6931	.049	.025	.044	.049	.050	.034	.810	.794	1.010	1.093	.813	.871	.037	.002	.013	.016	.025	.011	.943	.993	.972	.839	.241	.429
210	0.6777	.033	.055	.043	.039	.031	.062	.853	1.021	.627	1.122	1.085	1.168	.042	.004	.010	.019	.047	.035	.795	.318	.738	1.036	.251	.358
240	0.6969	.031	.042	.034	.049	.023	.055	.723	.878	.913	1.036	1.113	.784	.023	.012	.013	.010	.027	.012	.642	.777	.519	1.110	.799	.464
270	0.6980	.033	.028	.045	.047	.042	.037	.970	1.009	1.253	.990	1.002	.804	.045	.003	.038	.005	.019	.020	.831	.980	1.180	.542	.781	.783
300	0.6906	.027	.021	.060	.032	.029	.063	.510	.350	1.036	1.023	1.058	.726	.009	.015	.005	.006	.013	.018	.981	1.020	.395	.611	.749	1.123

Table 3: Effect of Av Changes in the Generation Size = 100 with Ideal Condition

B=1		Failure Rate						Repair Rate						Transition Rate						Preventive Maintenance Rate					
Parameters		λ_S	λ_C	λ_P	λ_B	λ_{SC}	λ_{PB}	μ_S	μ_C	μ_P	μ_B	μ_{SC}	μ_{PB}	ϕ_S	ϕ_C	ϕ_P	ϕ_B	ϕ_{SC}	ϕ_{PB}	η_S	η_C	η_P	η_B	η_{SC}	η_{PB}
N	AV P_{max}	.065	.040	.069	.066	.062	.067	1.150	1.138	1.290	1.158	1.144	1.224	.047	.041	.045	.044	.048	.049	1.120	1.170	1.350	1.120	1.150	1.240
	AV P_{min}	.025	.020	.029	.026	.022	.027	.150	.138	.290	.158	.144	.224	.007	.001	.005	.004	.008	.009	.120	.170	.350	.120	.150	.240
30	0.6830	0.027	0.039	0.046	0.065	0.031	0.037	1.128	0.449	0.914	1.153	0.881	0.960	0.016	0.018	0.043	0.012	0.039	0.015	0.235	1.120	0.645	1.094	0.799	1.194
60	0.7434	0.061	0.026	0.057	0.038	0.023	0.029	0.987	1.057	0.814	1.098	0.735	1.110	0.021	0.021	0.035	0.006	0.044	0.018	0.799	0.964	1.088	0.790	0.724	1.149
90	0.7107	0.045	0.021	0.039	0.040	0.050	0.030	0.744	0.902	0.859	0.698	0.983	0.490	0.012	0.022	0.016	0.035	0.046	0.030	0.983	0.880	1.175	0.756	1.002	0.676
120	0.7387	0.032	0.025	0.041	0.052	0.025	0.052	0.774	0.948	0.869	0.960	1.094	0.631	0.009	0.007	0.006	0.034	0.019	0.024	0.604	0.666	0.965	0.894	0.904	1.108
150	0.7356	0.027	0.053	0.030	0.037	0.033	0.055	0.960	0.641	1.146	1.137	0.770	0.965	0.043	0.016	0.005	0.006	0.027	0.017	0.848	0.909	1.171	1.041	0.553	1.015
180	0.7193	0.031	0.025	0.050	0.040	0.024	0.049	0.728	1.034	0.990	1.047	0.803	0.972	0.031	0.030	0.028	0.028	0.021	0.039	1.091	0.599	0.818	0.858	0.337	1.200
210	0.7141	0.028	0.042	0.049	0.030	0.022	0.054	0.432	1.097	0.984	0.733	0.735	0.574	0.043	0.003	0.010	0.013	0.022	0.034	1.004	0.496	1.156	0.904	1.140	0.985
240	0.7419	0.032	0.033	0.048	0.028	0.035	0.051	0.603	0.797	1.083	0.827	0.878	0.816	0.014	0.015	0.023	0.008	0.021	0.016	0.707	1.160	1.042	0.910	1.022	0.421
270	0.7617	0.039	0.023	0.047	0.046	0.025	0.027	0.848	0.755	0.691	1.021	1.119	0.906	0.013	0.008	0.013	0.010	0.012	0.020	0.407	0.876	1.190	0.902	0.661	0.326
300	0.7421	0.030	0.058	0.035	0.056	0.037	0.037	0.971	1.126	0.860	0.618	1.017	1.083	0.008	0.001	0.009	0.037	0.046	0.013	0.896	0.715	1.096	0.986	0.621	0.890

Table 4: Effect of Av Changes in the Generation Size = 270 with Faulty Condition

B=1		Failure Rate						Repair Rate						Transition Rate						Preventive Maintenance Rate					
Parameters		λ_S	λ_C	λ_P	λ_B	λ_{SC}	λ_{PB}	μ_S	μ_C	μ_P	μ_B	μ_{SC}	μ_{PB}	ϕ_S	ϕ_C	ϕ_P	ϕ_B	ϕ_{SC}	ϕ_{PB}	η_S	η_C	η_P	η_B	η_{SC}	η_{PB}
GN	AV P_{max}	.065	.040	.069	.066	.062	.067	1.150	1.138	1.290	1.158	1.144	1.224	.047	.041	.045	.044	.048	.049	1.120	1.170	1.350	1.120	1.150	1.240
	P_{min}	.025	.020	.029	.026	.022	.027	.150	.138	.290	.158	.144	.224	.007	.001	.005	.004	.008	.009	.120	.170	.350	.120	.150	.240
100	0.6769	0.041	0.028	0.046	0.027	0.054	0.042	0.689	1.097	1.021	1.148	0.595	1.129	0.029	0.008	0.014	0.007	0.045	0.013	0.550	0.605	0.497	0.447	0.410	1.164
200	0.6769	0.051	0.044	0.046	0.042	0.050	0.029	0.978	1.092	0.787	1.096	0.985	0.665	0.027	0.025	0.013	0.019	0.017	0.028	0.884	0.870	1.096	1.014	0.386	0.797
300	0.6792	0.026	0.031	0.029	0.041	0.050	0.060	0.553	0.986	1.118	1.074	1.003	0.837	0.035	0.006	0.009	0.022	0.018	0.032	1.059	0.522	0.834	0.492	0.537	1.160
400	0.6849	0.026	0.040	0.032	0.064	0.026	0.041	0.993	0.888	1.084	0.822	0.365	0.366	0.012	0.002	0.011	0.009	0.044	0.010	1.069	0.330	1.306	0.832	0.858	0.529
500	0.6889	0.029	0.042	0.037	0.031	0.037	0.046	0.896	1.115	1.048	0.772	0.942	0.841	0.035	0.002	0.016	0.035	0.036	0.030	1.005	0.761	1.119	0.903	0.780	0.926
600	0.6923	0.040	0.032	0.051	0.039	0.035	0.033	0.957	1.042	0.941	0.857	0.983	.097	0.024	.032	0.012	0.028	0.011	0.025	1.093	1.153	1.006	1.022	0.769	0.533
700	0.7038	0.034	0.031	0.032	0.030	0.055	0.036	1.085	0.942	0.528	0.677	0.857	1.014	0.012	0.001	0.029	0.008	0.020	0.018	0.976	0.182	0.955	0.724	0.920	0.987
800	0.7186	0.030	0.027	0.042	0.060	0.048	0.038	0.876	0.991	0.681	1.057	1.046	1.102	0.008	0.016	0.009	0.017	0.014	0.014	1.023	0.991	1.316	0.495	0.403	0.373
900	0.7264	0.032	0.023	0.033	0.044	0.044	0.048	1.026	0.976	0.643	1.063	0.631	0.781	0.009	0.006	0.006	0.006	0.020	0.037	0.484	0.479	0.412	0.652	0.598	1.165
1000	0.7325	0.047	0.024	0.050	0.034	0.045	0.056	0.778	1.104	0.873	0.841	1.056	1.081	0.011	0.005	0.010	0.004	0.041	0.027	0.829	1.018	0.404	0.671	0.573	0.922

Table 5: Effect of Av Changes in the Population Size=270 with Ideal Condition

B=0		Failure Rate						Repair Rate						Transition Rate						Preventive Maintenance Rate					
Parameters		λ_S	λ_C	λ_P	λ_B	λ_{SC}	λ_{PB}	μ_S	μ_C	μ_P	μ_B	μ_{SC}	μ_{PB}	ϕ_S	ϕ_C	ϕ_P	ϕ_B	ϕ_{SC}	ϕ_{PB}	η_S	η_C	η_P	η_B	η_{SC}	η_{PB}
GN	AV P_{max}	.065	.040	.069	.066	.062	.067	1.150	1.138	1.290	1.158	1.144	1.224	.047	.041	.045	.044	.048	.049	1.120	1.170	1.350	1.120	1.150	1.240
	P_{min}	.025	.020	.029	.026	.022	.027	.150	.138	.290	.158	.144	.224	.007	.001	.005	.004	.008	.009	.120	.170	.350	.120	.150	.240
100	0.7172	0.030	0.057	0.062	0.029	0.055	0.032	0.961	0.902	1.123	0.916	0.794	0.566	0.009	0.017	0.013	0.023	0.038	0.048	1.064	0.921	0.515	0.924	0.442	0.523
200	0.7274	0.053	0.023	0.039	0.037	0.033	0.033	0.760	0.534	1.209	0.668	0.848	0.797	0.019	0.005	0.008	0.033	0.045	0.039	0.592	0.482	1.221	0.956	0.183	0.260
300	0.7274	0.040	0.054	0.038	0.027	0.046	0.061	0.912	0.968	0.888	0.439	1.072	1.174	0.022	0.005	0.008	0.017	0.011	0.018	0.709	0.751	0.889	0.783	0.364	0.758
400	0.7367	0.028	0.023	0.062	0.057	0.022	0.041	0.937	1.006	0.601	1.097	1.128	1.004	0.015	0.009	0.009	0.027	0.025	0.043	1.057	0.298	0.942	1.010	0.786	0.867
500	0.7369	0.033	0.024	0.063	0.028	0.028	0.031	0.712	0.532	1.265	0.845	0.688	1.124	0.028	0.017	0.017	0.013	0.027	0.014	0.815	0.449	1.319	0.602	1.032	0.353
600	0.7372	0.025	0.021	0.051	0.056	0.044	0.039	1.013	1.023	1.231	1.029	0.876	1.112	0.022	0.015	0.023	0.013	0.018	0.011	0.785	0.465	0.455	1.052	0.166	0.515
700	0.7470	0.042	0.044	0.037	0.027	0.044	0.027	1.086	0.924	1.095	0.859	0.850	1.173	0.012	0.038	0.012	0.033	0.022	0.017	0.633	1.004	1.211	0.861	0.767	0.487
800	0.7490	0.027	0.020	0.035	0.044	0.036	0.032	0.709	0.430	0.941	0.966	0.539	1.188	0.033	0.001	0.006	0.012	0.028	0.012	0.788	1.135	1.028	0.700	0.868	0.744
900	0.7552	0.043	0.027	0.055	0.048	0.035	0.029	1.091	0.848	1.068	1.077	0.955	0.929	0.013	0.004	0.030	0.022	0.031	0.026	0.573	0.439	1.199	0.874	0.376	0.486
1000	0.7558	0.038	0.034	0.036	0.026	0.049	0.041	1.063	0.919	0.994	0.881	0.993	1.090	0.025	0.001	0.042	0.017	0.011	0.038	0.787	0.618	1.018	1.048	0.769	1.177

Table 6: Optimal Maintenance Parameters of the SMEs Manufacturing System in Population

Maintenance Parameters	Machine S	Machine C	Machine P	Machine B	Machine SC	Machine PB	AV %	X
Failure Rate (λ)	0.0336	0.0286	0.0456	0.0479	0.0425	0.037	69	1
Repair Rate (μ)	0.9705	1.0094	1.2533	0.9903	1.0027	0.8049		
Transition Rate (ϕ)	0.0452	0.0030	0.0387	0.0058	0.0196	0.0207		
PM Rate (η)	0.8310	0.9808	1.1803	0.5425	0.7818	0.7838		
Failure Rate (λ)	0.0396	0.0230	0.476	0.0465	0.0251	0.0277	76	0
Repair Rate (μ)	0.8483	0.7551	0.6910	1.0216	1.1191	0.9066		
Transition Rate (ϕ)	0.00137	0.0088	0.0131	0.0104	0.0121	0.0202		
PM rate (η)	0.4075	0.8761	1.1901	0.9024	0.6615	0.3261		

Table 7: Optimal Maintenance Parameters of the SMEs Manufacturing System in Generation

Maintenance Parameters	Machine S	Machine C	Machine P	Machine B	Machine SC	Machine PB	AV %	X
Failure Rate (λ)	0.0477	0.0249	0.0509	0.0344	0.0454	0.0561	73	1
Repair Rate (μ)	0.7789	1.1043	0.8739	0.8416	1.0565	1.0817		
Transition Rate (ϕ)	0.0311	0.0050	0.0102	0.0041	0.0415	0.0273		
PM Rate (η)	0.8291	1.0189	0.4048	0.6716	0.5735	0.9226		
Failure Rate (λ)	0.0387	0.0345	0.0360	0.0261	0.0496	0.0411	75	0
Transition Rate (ϕ)	0.0255	0.0016	0.0423	0.0173	0.0110	0.0384		
PM Rate (η)	0.7870	0.6189	1.0180	1.0481	0.7691	1.1779		

5.3 Managerial Implication

Based on the proposed optimization-based maintenance decision-support framework, several managerial implications and operational benefits were observed in the selected manufacturing plant. These outcomes support strategic maintenance planning, cost optimization, and system reliability enhancement in the industrial environment.

1. By enabling condition-based and predictive maintenance techniques, the optimized maintenance decision-making framework greatly lowers unplanned machine breakdowns. As a result, it increases labor productivity and operational efficiency by minimizing unscheduled downtime and lowering reliance on emergency repair workforce deployment.
2. The optimized maintenance policy derived from the research outcomes facilitates structured financial planning related to maintenance investments. It supports the development of systematic maintenance budgeting and spare parts inventory strategies, thereby reducing unforeseen expenditure on corrective maintenance and emergency service activities.
3. Effective spare parts availability planning is made possible by predicting the Remaining Useful Life (RUL) of crucial subsystems and machine components. By guaranteeing the timely acquisition and availability of service components, this predictive solution enhances inventory control by lowering lead times and maintenance disruptions.
4. The research analysis identifies the optimal maintenance parameters of critical subsystems based on availability sensitivity analysis of the manufacturing system. These optimized parameters enable accurate estimation of both theoretical and practical Remaining Useful Life of critical equipment. Furthermore, the optimized maintenance parameters are integrated with Industrial Internet of Things (IIoT)-enabled monitoring systems. This integration enhances real-time condition monitoring, supports predictive maintenance scheduling, and optimizes spare parts inventory management by maintaining high availability levels of critical subsystem components within the maintenance management framework

6. Conclusion

This research study presents the development and implementation of a Genetic Algorithm (GA)-based optimization framework to perform Reliability, Availability, and Maintainability (RAM) analysis for enhancing the maintenance management strategy of complex machine subsystems in a cross-member component production unit operating within Small and Medium Enterprises (SMEs) of the sheet metal forming industry in the southern region of Tamil Nadu, India. The proposed analytical framework integrates Markov Decision Process (MDP)-based availability modelling with evolutionary optimization techniques to identify the optimal maintenance parameters governing

system performance. The study primarily focuses on determining the optimal values of failure rate, repair rate, transition rate, and preventive maintenance rate to maximize the operational availability of the manufacturing system. The results of the optimization analysis demonstrate that the GA-based RAM model effectively predicts system performance variations under both faulty and ideal operating conditions. The availability of the cross-member production system was observed to reach 73.25% under faulty operational conditions, while the availability increased to 76.17% under ideal maintenance conditions. These results indicate a significant improvement in system performance achieved through the identification and application of optimized maintenance parameters. The optimized parameter set provides a quantitative decision-support mechanism for maintenance planning and contributes to improved reliability and reduced system degradation of critical machine components.

Furthermore, the proposed optimization framework enables the development of a structured preventive maintenance management model tailored for SMEs operating in resource-constrained environments. The implementation of this optimized maintenance decision-support system assists maintenance engineers and plant management teams in improving equipment efficiency, minimizing unexpected machine failures, and reducing production interruptions. The model also supports workforce optimization by reducing emergency maintenance interventions and improving maintenance scheduling effectiveness. The findings of this research confirm that the integration of GA-based optimization with RAM analysis provides a robust methodology for enhancing maintenance performance in manufacturing systems involving multi-state machine components. The proposed decision-making framework significantly reduces machine downtime, production delays, and maintenance operational costs, thereby improving overall plant productivity and sustainability.

For future research directions, the developed methodology can be extended to evaluate availability variations at the subsystem and component levels of critical manufacturing equipment. Although this study employs a widely accepted Non-Traditional Optimization Technique (Genetic Algorithm), the framework can be further enhanced by integrating advanced Nature-Inspired Algorithms (NIA) to improve optimization accuracy and convergence efficiency. Additionally, the predicted optimal maintenance parameters can be integrated into real-time monitoring systems through Industrial Internet of Things (IIoT) platforms supported by programmable embedded hardware such as microcontroller-based circuit boards and Arduino-enabled sensor modules. This integration can facilitate predictive maintenance implementation, autonomous preventive maintenance scheduling, and smart maintenance management systems, thereby supporting the transition toward Industry 4.0-enabled intelligent manufacturing environments.

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