

## Research Article

# Availability Analysis of the Critical Production System in SMEs Using the Markov Decision Model

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Small and medium-sized enterprises (SMEs) in today's world have numerous issues in ensuring the availability and safety of critical machines and their components in the working environment. As a result, SMEs considered planning and scheduling maintenance tasks to be a significant threat. The goal of this research is to identify the critical subsystem of the automobile spare parts production plant in the southern region of Tamil Nadu, India, and then to prioritize the maintenance activity and set up an architecture for autonomous preventive maintenance (PM) in SMEs that includes an optimal decision support system. The transition state diagram of the individual and simultaneous production system has been developed with the application of the Markov decision model approach. It was used to analyze the present variables of the production systems and forecast the optimal maintenance parameters such as the failure rate and the repair rate, through the production system's availability analysis. This availability analysis reveals that system B (Piercing) is classified as the most critical because of the abrupt availability variation compared to all other production systems, concerning the corresponding maintenance parameters such as a failure rate of 0.0371, a repair rate of 0.7094, and the availability of the piercing system of 0.5056. Finally, the use of an autonomous PM management system and the most effective maintenance workforce has enhanced productivity and customer satisfaction in SMEs. The predictive maintenance management system has been further investigated to determine the real-time remaining useful life (RUL) of critical systems in the automobile spare parts manufacturing plant in the southern region of Tamil Nadu, India.

## 1. Introduction

Due to the tremendous growth of the human population, manufacturing, and production industries have exploded over the world. Most manufacturing industries are keen to implement a smart and effective maintenance process in the manufacturing industry's shop floor area to improve productivity, employee performance, customer satisfaction and reduce machine idle time and production delays, according to the newest trend [1]. The most significant responsibilities in the factory are maintenance management systems and

determining the residual effective life of critical components. Sudden failures of the manufacturing plant's critical system and its components resulted in capital expenditure and unplanned manufacturing production losses [2]. To reduce capital expenditure, sudden failure, and idle time of important systems and their components in the industry, a planned and preventive maintenance strategy must be implemented. Sudden failures of critical systems and their mechanical components are extremely risky, since they can wipe out a whole manufacturing process sequence in SMEs. Most engineers, scientists, and researchers are keen to

provide such a new optimal framework for the most critical systems in a manufacturing plant's reliability and availability process. In the industry, effective preventive maintenance (PM) planning and scheduling techniques reduce unplanned workforce and production delays. In today's competitive manufacturing world, achieving optimum reliability of complex systems is critical. Maintenance employees' working hours might be scheduled to ensure optimal reliability and availability of complicated systems.

Maintenance is described as restoring or retaining machine components to their original condition by routine testing and operation in the industry, according to numerous definitions. PM and corrective maintenance (CM) are the two types of maintenance. PM is further divided into two types: conditional based maintenance (CBM) and age-based maintenance (ABM). The ABM function of complex systems in manufacturing plants is the focus of this research [3]. The Markov birth-death technique is used to organize the availability modeling of complex systems. The transition state diagram of a given manufacturing system is used to generate mathematical models of complicated systems in the production process using first-order differential equations. To find the best solution for a specific availability simulation, these equations are solved using MATLAB R2019a software [4]. This study looks at three different forms of conditioning machines: (a) In that case, the original or raw level machines are ready to "operate the state." (b) The equipment has minor flaws, but it is still operational "under maintenance conditions." (b) In that case, the machine has a major flaw and cannot function in a "failed state." The IIoT is used to continuously monitor complex system behavior, utilization, and equipment downtime. For the autonomous human-machine communication of a complex system, ICT is used. This research simulation focuses on new autonomous PM with the optimal decision-making process of complex systems in the manufacturing plant.

The most important component of this research is determining the availability variation of specific machines to pinpoint the manufacturing plant's critical subsystems. Install continuous monitoring systems in important subsystems to achieve the best PM planning and scheduling procedure in the industry. Then, based on this research prediction, organize the most appropriate and effective manpower distribution of maintenance teams in the specified manufacturing plant. The Markov birth-death process (MBDP) is a frequently used technique for evaluating machine and component reliability, availability, and maintainability (RAM). Based on availability changes, this research examines the performance of specific computers. The goal of this research is to determine the best PM management with an optimal decision-making process framework for shop floor operations. The goal of the maintenance department in the industry is to increase the productivity of the manufacturing facility through appropriate manpower allocation. Finally, in small and midsize enterprises, organize an autonomous and optimal PM schedule to improve manufacturing machine performance, maintenance team productivity, and customer satisfaction.

The following is how the rest of this research study is structured: The next part contains reviews of important literature for this research activity and research gap. In Section 3, the sequence of this study analysis and manufacturing procedure is described as a problem report. The proposed smart maintenance approach to the manufacturing system is outlined in Section 4. Sections 5 and 6 present mathematical modeling, numerical results, application, proposed simulation of the complex system in SMEs, and results and discussion. Finally, the conclusion, limitations, and future scope of this availability simulation research of critical part production systems in SMEs are presented in Section 7.

## 2. Review of Literature

To begin, we added recent research work on the automobile parts manufacturing industry's product functionality and preventive maintenance upgrades to broaden our survey of the literature. Given the context of our research, some relevant research on production and PM schedules for the degradation of critical machine components is considered.

The application of the net present value technique for the critical component economic analysis has been explained for the maintenance cost and economic analysis of the multiple aspects that affect the efficiency of the coal-fired thermal power plant [5]. Then, based on the violation of the biochemical oxygen demand standards, critical issues in the reliability and maintenance analysis of the Waste-Water Treatment Plant in Tehran West Town were described [6] and analyzed some critical factors (operational failure, mechanical equipment, and design deficiencies) using the fault tree analysis with top-down approach. The efficient route planning model for mobile agents on the Internet of Things (IoT) has been explained using the Markov decision process (MDP) and analyzed two stages of the mechanism initially, clustering the IoT source data from the sink and grouping the data head through the angle-based process of the mobile agent assignment. MDP is used in the second stage to anticipate the most efficient and optimal route planning for the use of the mobile agent. Through the use of the partially observable Markov decision process and partially observable Monte Carlo planning [7], the management category of bug notifications in software usage has been explored. They examined a lot of bug messages from firebox software and prioritized problem-solving strategies according to how important the bugs' signals were [8]. They exhibited the new optimization methodology of risk-based maintenance management systems of the components in the chemical plant's natural gas regulating and metering station in another investigation. They used the dynamic Bayesian network model to analyze the process variables, failures, and corrective maintenance functions, as well as the influence diagrams of the critical components and MDP, and to propose the best maintenance scheduling process in the natural gas regulating and metering station [9]. The working process, performance, long-term availability, and maintainability of water treatment plant (WTP) machine components have been investigated and have analyzed the

individual operations of WTP using the reliability block diagram and semi-Markov process to predict the availability analysis in WTP in the Netherlands [10].

The RUL prediction of the continuous condition deteriorating the critical engineering system has been explained. They used the discrete-time Markov chain process and semi-Markov decision process (SMDP) to analyze aviation and aerospace vehicle systems under various dynamic operational situations to develop a new RUL prediction model and optimal maintenance planning for critical engineering systems [11]. The single vacant taxi routing difficulties in Shanghai were explored and value iteration algorithms were used to analyze the existing taxi routing problems. They have implemented and proposed the optimal solution to the existing single vacant taxi routing problem using MDP in the cab travel agency as a result of their research [12]. The most critical components (turbocharger, cylinder, and governor) of the thermal power plant were investigated and analyzed using the time between overhaul approach and SMDP to propose the suitable and optimal decision-making process for maintenance in the thermal power plant [13]. The opportunistic maintenance (OM) policy of two series systems in the turbine was described. They compared the two separate units of maintenance policies to the other maintenance systems using the age-based maintenance policy. SMDP used it to estimate the wind turbine's critical components and offered a new framework for the optimal CM, PM, and OM strategies [14]. The critical overviewed the number of studies on performance modeling RAM and economic analysis of critical subsystems in coal-fired thermal power plants [15]. Another research examined the predicting concerns of a manufacturing plant based on quality issues. They then analyzed production, failure, and defect rates to organize maintenance strategy optimization with the lowest production and maintenance costs in the industry [16]. The Markov modeling and availability analysis of urea production systems in the fertilizer manufacturing facility were explained. They investigated these subsystems using MBDP to organize the best fertilizer maintenance approach [17].

Similarly, the planning and scheduling of the maintenance management system, as well as the implementation of the water treatment main system, were investigated using MDP in conjunction with the traditional dynamic programming model to propose the best decision-making framework for the given system's maintenance policy [18]. The optimal maintenance scheduling policy and RAM analysis of the critical machine subsystem in SMEs have been described, and they analyzed the RAM of the machine subsystem based on availability changes using MDP with the addition of new constraints (simultaneous machine failure condition) and mathematical equations solved by MATLAB software. They predicted the most crucial subsystem in the machine based on the findings in order to organize sustainable and optimal maintenance decision-making processes for SMEs [19, 20]. Similarly, performance modeling and availability analysis of malt mill systems in the brewery production plant has been explored and used by the Markov model approach to analyze the complete

system of the brewery plant to determine the most critical subsystem in the working plant [20]. The heated holdup tank's predictive maintenance (PdM) management system in a thermal power plant has been explored. They used the piecewise-deterministic Markov process to analyze the subsystems (inlet pumps, control valves) of a thermal power plant and offer the best decision-making for PdM in a power plant [21].

Similarly, the performance and availability analysis of repairable components in the manufacturing system described and analyzed the three modes of the repairable system (time to failure, time to repair, and time to delay) using the Markov process to propose the best analytical framework for the availability and maintainability implementation in the repairable system [22]. The data-driven methodology for evaluating tool wear status and predicting tool RUL has been explained through the use of real-time sensor data analysis combined with a machine-learning algorithm [23]. The reliability and availability analysis of the Uncaser system of the beer manufacturing process in the brewery production plant has investigated and analyzed the entire subsystems using MBDP and MATLAB software to predict the most critical subsystems in the brewery production plant [24]. The optimal integrated manufacturing and maintenance policy for wind turbines was created in a separate study. They use a cost model of wind farms to investigate the relationship between energy changes in the production rate and the failure rate of wind turbines, and they also explored the best-integrated lot sizing and maintenance approach for multi-machine systems in terms of energy consumption [25]. The periodic dynamic imperfect preventive maintenance model of wind turbines was investigated. They built the model based on the analysis of actual wind farm maintenance data in order to reduce maintenance costs and assure maximum availability of wind turbines [26]. Using the metaheuristic algorithm, the optimization of the two stages of assembly system maintenance planning has been described. They analyze the risk assessment factors in the assembly system to build the best preventive maintenance plan [27]. Finally, in the automobile spare parts manufacturing industry, the performance design and availability analysis of crank-case manufacturing systems has been investigated and analyzed the normal working state and the partially failed state of the subsystems in the crank-case manufacturing system through the application of MDP to reduce equipment failures, improve the RUL of the equipment and maximize the availability of the given system [28]. The simulation analysis of the smart manufacturing systems with the integration of the IoT framework challenges and advantages has been described for achieving the low-cost minimum risk in the production environment [29]. Smart predictive maintenance with the optimal scheduling process of the industry has been described. Through the smart maintenance management system, the computer integrated the planning and scheduling process of the maintenance and manufacturing activities in the industry [30]. A new preventive maintenance strategy for the industry has been explained with the application of the hidden Markov model. The reliability of the systems has been

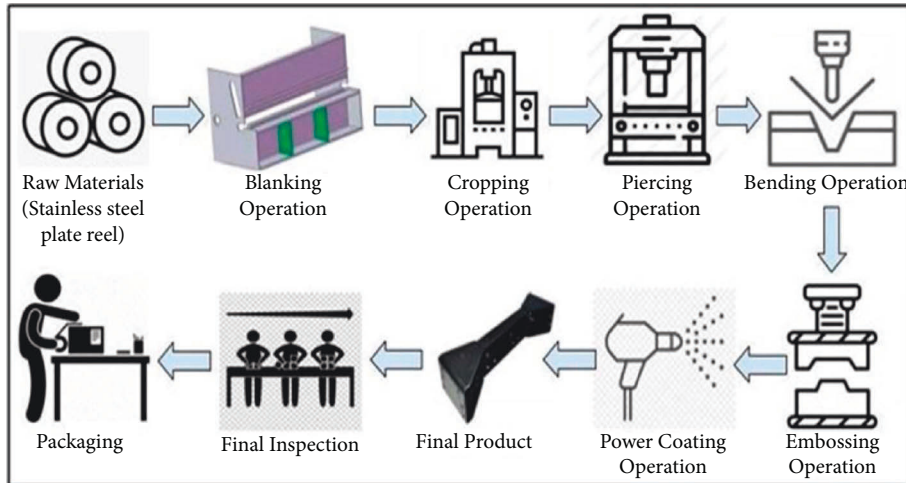


FIGURE 1: The manufacturing flow process of the cross-member part production.

measured through the maximum likelihood estimator. They developed the simulation for the better performance of the maintenance management system [31]. The optimal design of the condition-based maintenance model has been illustrated through the application of the piecewise-deterministic Markov process in the field of civil engineering construction of roads and bridges [32]. The detailed overview of the smart maintenance management system and the factor analysis of the implementation of the smart maintenance managements has been explained. The human error factors are evaluated for developing the best maintenance scheduling and planning in the industry [33, 34]. Through this systematic literature review process, recent research in the field of smart maintenance and management has been dealt with and predicted the future scope, challenges, and the research gap of this real-time industrial case study research study also be elaborated on in the next section.

**2.1. Research Gap.** Various mathematical strategies are efficiently employed to measure machine RAM for an optimal PM management system, according to reviews of recently published research articles. They are also employed in the large-scale industry, high-end original equipment manufacturing, off-source wind farms, mining, shipbuilding, and aircraft construction. No previous research article has recorded more than one system failure (simultaneous failure) at the same time in the availability prediction equations, according to our findings. The state of the small and medium-scale manufacturing industry causes failures. This research article was proposed to address a research gap. The goal of this study article is to identify the most critical systems in the manufacturing plant and improve the maintenance management system with optimal decision-making processes in SMEs. Furthermore, using the Markov decision model and the latest technologies (Industry 4.0) such as the industrial Internet of Things and Internet communication technology, this study examined a real-time case study on the sheet metal forming industry. The next section contains detailed explanations of this study.

**2.2. Production Model.** The purpose of this real-time case study research is to look at the industry of the sheet metal forming industry. They produced a more number of automobile spare parts. In the automotive parts manufacturing sector, the cross-member product is the most significant manufacturing unit. The implementation of this research began in an automobile spare part production plant due to the real-time case study, but it may be applied to a variety of manufacturing industries. Shearing, cropping, piercing, bending, embossing, powder coating, final inspection, and packaging are among the production activities for cross-member parts. These forming operations are carried out on the shop floor with a variety of hydraulic and pneumatic pressing systems ranging in size from 100 to 500 tones, as well as a variety of tools and dies. Figure 1 depicts the manufacturing flow method for cross-member part production and the description of the manufacturing process has been illustrated below. During the production of this product, four systems are used. The RUL of the most important mechanical components determines the service and maintenance policy for each system.

**2.3. Raw Material.** The selected forming industry (Sun Pressing Private Limited, Madurai) produced numerous automobile parts like fuel tank mounding, break petals, clamp, engine mounting, etc., through the application of the sheet metal forming process. In this real-time case study, the cross-member part production plant has been chosen. For that part of the production, the raw material (steel and stainless-steel sheets) is used for making that product and it is used in 8 mm to 12 mm thick stainless-steel sheets with various cross-sectional dimensions as per the product designs and diagram of the cross-member part.

**2.4. Shearing or Blanking.** Initially, the raw materials (stainless-steel sheets or plates) are cut into the required dimensions length ( $L$ ) and breath ( $B$ ), as per the standard specification of the given drawing, through the utilization of

the semi-automatic (250 Ton) hydraulic shearing or blanking machine (Machine A).

**2.4.1. Cropping.** In this section, the sheared plates are moved to the cropping operation, based on the standard specification diagram the corners or sharp edges of the plate have been modified with a curved shape as per the design, by using the pedal-operated (150 Ton) hydraulic pressing machine (Machine B).

**2.4.2. Piercing.** After the cropping process, that cropped plate is moved to the piercing operations. In that situation, the required shape and various dimensions of the holes have been produced through this process with the help of the (200 Ton) hydraulic pressing machine (Machine C).

**2.4.3. Bending.** In this section, the pierced plates have been moving into the profile forming operation, and the final shape of the product was achieved through the utilization of an automatic controlled (250 Ton) hydraulic pressing machine (Machine D). Once this process is completed, the final product will be produced in the manufacturing plant.

**2.4.4. Embossing.** In this section, the final part of the cross-member has been embossed with the logo of the company, part number, date, month, year of production, and position symbol with the help of (150 Ton) autonomous pneumatic pressing machine in the forming industry.

**2.4.5. Powder Coating.** After the embossing operation, the final cross-member part moves to the following manual assembly operations like welding, reverting, drilling, and subsequently to the cleaning process, then the powder coating process.

**2.4.6. Final Inspection and Packaging.** Finally, that cross-member part moves to the visual quality inspection process based on the stand operating procedure, and after satisfying the quality requirements that cross-member part moves to the packaging section, where it is packed and shipped to the customer.

The goal is to design an optimal maintenance management system procedure for the critical system in the manufacturing plant, which is based on the RUL of mechanical components, in order to maximize profit and productivity on the shop floor. In the following sections, the manufacturing model's availability analysis and the RUL calculation of the production system and its components should be established.

**2.5. Problem Formulation.** The assumptions that will be utilized to develop the PM management system with an optimal decision-making process of the production model will be supplied first. The automobile spare part (cross-member) manufacturing process is briefly outlined, as well

as the system maintenance problems. The following assumptions are supported by this availability analysis of the maintenance model:

- (1) Initially, each critical system was in good working order (A, B, C, D, AB, and CD).
- (2) The repair rate and the failure rate of each complex system are constant and statistically independent ( $\lambda_M, \mu_M$ ) ( $M = A, B, C, D, AB, \text{ and } CM$ ).
- (3) Every repaired system is treated as if it were completely new.
- (4) The system's PM activity will be managed by a single maintenance team.
- (5) Original, under maintenance, and repair (e.g., A,  $\underline{a}$ , and  $a^*$ ) are the three states of every critical system.
- (6) Simultaneous failure of the necessary systems (AB and CD) is also taken into account.
- (7) The rate of PM and critical system transition is assumed to be constant ( $\eta_M, \phi_M = \text{Constant}$ ).

### 3. Materials and Methodology

The optimal decision-making process of the maintenance method for this real-time industrial research study consists of the significant preliminary data preparation process, which includes numerous research practice sequences as follows.

**3.1. Data Collection.** The last year's (2020 to 2021) system maintenance and utility information of chosen complicated automobile spare part production systems were obtained from the maintenance department based on historical record sheets, personal system running time, system idle time, correct maintenance time, and PM schedules in the production line.

**3.2. Preliminary Data Analysis.** In order to conduct an adequate study of the production system's reliability and availability, a preprocessing of data has been carried out. The offered maintenance history sheet contains complete automobile parts manufacturing system maintenance data. In that case, groups of system data are categorized independently for our availability analysis purposes, and we use this data to calculate individual critical system repair rate, failure rate, and PM rates using the mathematical formula presented in equations (1) and (2).

The ratio of total failures (P) that occur on the complicated system to total maintenance time (Q) of that critical system of the production plant is defined as the repair rate ( $\mu_A$ ) of the individual complex system of the automobile spare parts manufacturing unit. The shearing operation system attains 228 failures in one-year production, and the annual production schedule of that system A includes 5 days of system maintenance per month. The repair rate ( $\mu_A = 0.158$ ) of a certain system (shearing operation) in the automobile spare parts manufacturing plant is measured.

TABLE 1: The parameters of the automobile part manufacturing unit's maintenance.

| System    | Total numbers of failures per year (P) | Total maintenance time per year (Q) Hrs | Total utilization time per year (R) Hrs | Rate of repair ( $\mu$ ) P/Q | Rate of failure ( $\lambda$ ) P/R |
|-----------|--|---|---|------------------------------|-----------------------------------|
| System A  | 228                                    | 1440                                    | 8640                                    | 0.158                        | 0.026                             |
| System B  | 120                                    | 864                                     | 5760                                    | 0.138                        | 0.020                             |
| System C  | 216                                    | 1440                                    | 8640                                    | 0.150                        | 0.025                             |
| System D  | 84                                     | 288                                     | 2880                                    | 0.290                        | 0.029                             |
| System AB | 168                                    | 1152                                    | 7200                                    | 0.145                        | 0.023                             |
| System CD | 156                                    | 864                                     | 5760                                    | 0.090                        | 0.027                             |

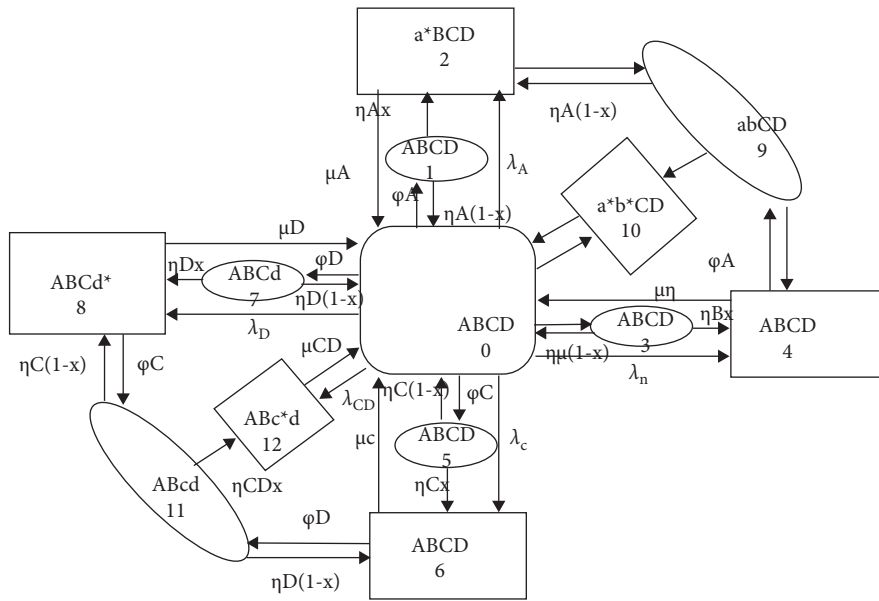


FIGURE 2: The critical component production system transition state diagram.

The repair rate estimation of the shearing operation system mathematical expression is as follows:

$$\mu_A = \left(\frac{P}{Q}\right) = \left(\frac{228}{1440}\right) = 0.158. \quad (1)$$

The shearing operation system failure rate ( $\mu_A$ ) is 0.158 per hour. Similarly, the repair rates of all other automobile spare parts manufacturing systems are calculated using equation (1).

The ratio of the total number of failures ( $P$ ) occurring on the complicated system to the total usage time ( $R$ ) of that critical system in the manufacturing unit is the failure rate ( $\lambda_A$ ) of the individual complex system of the automobile spare parts production unit. Throughout the year, the shearing operation system experiences 228 failures, and it operates in the manufacturing unit 24 hours a day, 30 days a month, measuring the shearing operation system-specific failure rate ( $\lambda_A = 0.026$ ). The failure rate measuring equations of the shearing operation system mathematical expression is described further down.

$$\lambda_A = \left(\frac{P}{R}\right) = \left(\frac{228}{8640}\right) = 0.026. \quad (2)$$

The failure rate of the shearing operation system ( $\lambda_A$ ) is 0.026 failures per hour. Equation (2) is also used to calculate the failure rates of the other production systems and (Table 1) shows the maintenance parameters for the vehicle spare part production unit.

**3.3. Mathematical Modeling.** This section consists of a detailed illustration of the mathematical formulation of the availability analysis of the manufacturing system and the numerical result of this real-time case study. The measuring of the availability of the individual production system is analyzed through the Markov decision process. Through this availability analysis, the significant or most critical systems have been identified based on the availability variations.

#### 4. Availability Analysis Formulation of the Production System

The essential system's transition state diagram is shown in (Figure 2). The first-order differential availability analytical equations of the critical systems in the automobile spare parts manufacturing plant are generated using this transition state diagram, which comprises three-phase operations

(original, reduced capacity, and failure). First-order differential equations are used to produce mathematical equations in the availability analytics of the manufacturing system [4]. Here only the faulty condition of the system equations are described in detail. Due to the minimal variation and negligible maintenance parameters of the manufacturing system, the formulation of the ideal condition of the system has been ignored in the given mathematical formulations. Finally, using the Markov decision model, the future behavior of the present critical part manufacturing system was analyzed. All essential part manufacturing systems evaluate three states in this scenario, original, under maintenance, and ineffective.

In this MDP, the availability prediction equations are generated through the utilization of the transition state diagram (TSD) of the manufacturing system. In this TSD each manufacturing machines consist of three state conditions, namely, (1) original or good state as a 0, (2) under maintenance state as an odd state 1, 3, 5,..etc., (3) failed state as an even state 2, 4, 6, .. etc. Initially, system A starts its transformation from the original state to the under maintenance state concerning the transition rate and the PM rate of that machine. If that transformation is negligible or minimum down time, it will again go to the original state condition. Otherwise, that machine moves to the failed state condition. Once that machine failure has been rectified, further it goes to the original state concerning the failure rate and the repair rate of that machine, and that machine is considered as the new or original state machines.

The probability function of system A is starting the conversion from the original or operative state to a reduced capacity state and that mathematical equation is explained as

$$\eta_A P_1(t) = \varnothing_A P_0(t). \quad (3)$$

The probability function of system A is starting the conversion from the reduced-capacity state to the failed state after the maintenance function and that system gets restored to the original state of the mathematical equation explained as

$$\mu_A P_2(t) = \eta_A x P_1(t) + \lambda_A P_0(t). \quad (4)$$

Similarly, the availability measuring equations of the other systems B, C, D, AB, are CD are derived from the transition state diagram as shown in (Figure 2).

Applying the Laplace transform of the above (3) and (4) equations, we get

$$\eta_A P_1(S) = \varnothing_A P_0(S), \quad (5)$$

$$\mu_A P_2(S) = \eta_A x P_1(S) + \lambda_A P_0(S). \quad (6)$$

**4.1. Steady-State Condition of a Critical Part Production System.** The manufacturing of the critical component of all the subsystems is a steady-state process. All system transition times are assumed to be zero and through applying  $t=0$  in all of these conditions at equilibrium in equations (5) and (6). Finally, we establish the critical part of manufacturing

systems' equilibrium probability equations.  $dp/dt = 0, t \rightarrow \infty$ , such as following equations:

$$\eta_A P_1 = \varnothing_A P_0, \quad (7)$$

$$\mu_A P_2 = \eta_A x P_1 + \lambda_A P_0. \quad (8)$$

The above mathematical equations (7) and (8) are solved recursively for predicting the individual system probability function like P1, P2, P3, P4, P5,.... P12,

$$P_j = E_j P_0, \quad (9)$$

where ( $j = 1.2.3. \dots 12$ ),

$$P_1 = \frac{\varnothing_A P_0}{\eta_A}; P_2 = \frac{\eta_A x P_1 + \lambda_A P_0}{\mu_A}; \quad (10)$$

$$p = (P_1 + P_2 + P_3 + P_4 + P_5 + \dots + P_{12}) P_0.$$

The default state of the above equations is used after obtaining the static-level probability equations of critical part production systems. The following is a description of the normalization level equation: the sum of the critical part production systems probabilities equals one.

#### 4.2. Using the Normalization Position

$$\sum_{i=1}^{12} P_i = 1$$

$$P_0 = \left[ 1 + \sum_{i=1}^{12} P_i \right]^{-1} \quad (11)$$

$$Av = P_0.$$

Availability of the system = (Faulty  $x = 1$ ), Availability of the system = (Ideal  $x = 0$ ).

### 5. The Numerical Results of the Critical Part Production Model

The equations use the numerical values of individual automobile spare parts manufacturing systems to measure and analyze the availability changes of the critical part production system in the sheet metal forming industry. (Table 2) displays the numerical input values. The availability measurement equations with two separate situations, the systems in the faulty position, use these standard values directly. MATLAB R2019a software is then used to categorize these data into higher models with our control constraints. Equations (3) to (8) employ these randomly generated variables to determine the optimal and greatest availability of a given automobile spare part production system for SMEs.

In this research study, we have analyzed all the systems of the given manufacturing model in the industry. But only system B and system D have been explained in detail in this manuscript because all other systems have a uniform variation of the availability concerning the maintenance parameters (the repair rate and the failure rate) of the respective system. Only these above two systems had abrupt

TABLE 2: Input numeric values for the system’s availability analysis.

| Systems    | Repair rate ( $\mu$ ) | Failure rate ( $\lambda$ ) | Transition rate ( $\emptyset$ ) | Preventive maintenance rate ( $\eta$ ) |
|------------|-----------------------|----------------------------|---------------------------------|--|
| System A   | 0.158                 | 0.026                      | 0.008                           | 0.15                                   |
| System B   | 0.138                 | 0.020                      | 0.001                           | 0.17                                   |
| System C   | 0.150                 | 0.025                      | 0.007                           | 0.12                                   |
| System D   | 0.290                 | 0.029                      | 0.005                           | 0.35                                   |
| System A&B | 0.144                 | 0.022                      | 0.008                           | 0.15                                   |
| System C&D | 0.224                 | 0.027                      | 0.009                           | 0.24                                   |

TABLE 3: The impact of system B availability variation in the faulty position.

| $\lambda_{B\mu_B}$ | 0.020 | 0.022 | 0.025 | 0.028 | 0.031 | 0.034 | 0.037 | 0.040 |
|--------------------|-------|-------|-------|-------|-------|-------|-------|-------|
| 0.138              | 0.485 | 0.480 | 0.476 | 0.471 | 0.466 | 0.462 | 0.458 | 0.453 |
| 0.209              | 0.497 | 0.494 | 0.491 | 0.487 | 0.484 | 0.481 | 0.478 | 0.475 |
| 0.280              | 0.503 | 0.501 | 0.498 | 0.496 | 0.493 | 0.491 | 0.488 | 0.486 |
| 0.352              | 0.507 | 0.505 | 0.503 | 0.501 | 0.499 | 0.497 | 0.495 | 0.493 |
| 0.423              | 0.509 | 0.508 | 0.504 | 0.504 | 0.503 | 0.501 | 0.499 | 0.497 |
| 0.495              | 0.511 | 0.510 | 0.508 | 0.507 | 0.505 | 0.504 | 0.502 | 0.501 |
| 0.566              | 0.513 | 0.511 | 0.510 | 0.509 | 0.507 | 0.506 | 0.505 | 0.503 |
| 0.638              | 0.514 | 0.512 | 0.511 | 0.510 | 0.509 | 0.508 | 0.507 | 0.505 |
| 0.709              | 0.515 | 0.513 | 0.512 | 0.511 | 0.510 | 0.509 | 0.508 | 0.507 |
| 0.780              | 0.516 | 0.514 | 0.513 | 0.512 | 0.511 | 0.510 | 0.509 | 0.508 |
| 0.852              | 0.517 | 0.515 | 0.514 | 0.513 | 0.512 | 0.511 | 0.510 | 0.511 |
| 0.923              | 0.517 | 0.515 | 0.515 | 0.514 | 0.513 | 0.512 | 0.511 | 0.512 |
| 0.995              | 0.518 | 0.516 | 0.515 | 0.514 | 0.514 | 0.513 | 0.512 | 0.511 |
| 1.066              | 0.517 | 0.516 | 0.516 | 0.515 | 0.514 | 0.513 | 0.513 | 0.512 |
| 1.138              | 0.517 | 0.517 | 0.516 | 0.515 | 0.515 | 0.514 | 0.513 | 0.513 |

TABLE 4: The impact of system B availability variation in the faulty position.

| $\lambda_{B\mu_B}$ | 0.040 | 0.042 | 0.045 | 0.048 | 0.051 | 0.054 | 0.057 | 0.060 |
|--------------------|-------|-------|-------|-------|-------|-------|-------|-------|
| 0.138              | 0.453 | 0.449 | 0.445 | 0.441 | 0.437 | 0.433 | 0.429 | 0.425 |
| 0.209              | 0.475 | 0.472 | 0.469 | 0.466 | 0.463 | 0.460 | 0.457 | 0.434 |
| 0.280              | 0.486 | 0.483 | 0.481 | 0.479 | 0.476 | 0.474 | 0.472 | 0.470 |
| 0.352              | 0.493 | 0.491 | 0.489 | 0.487 | 0.485 | 0.483 | 0.481 | 0.479 |
| 0.423              | 0.497 | 0.496 | 0.494 | 0.493 | 0.491 | 0.489 | 0.488 | 0.486 |
| 0.495              | 0.501 | 0.499 | 0.498 | 0.497 | 0.495 | 0.494 | 0.492 | 0.491 |
| 0.566              | 0.503 | 0.502 | 0.501 | 0.500 | 0.498 | 0.497 | 0.496 | 0.495 |
| 0.638              | 0.505 | 0.504 | 0.503 | 0.502 | 0.501 | 0.500 | 0.499 | 0.498 |
| 0.709              | 0.507 | 0.506 | 0.505 | 0.504 | 0.503 | 0.502 | 0.501 | 0.500 |
| 0.780              | 0.508 | 0.507 | 0.507 | 0.506 | 0.505 | 0.504 | 0.503 | 0.502 |
| 0.852              | 0.510 | 0.509 | 0.508 | 0.507 | 0.506 | 0.505 | 0.504 | 0.504 |
| 0.923              | 0.511 | 0.510 | 0.509 | 0.508 | 0.507 | 0.506 | 0.506 | 0.505 |
| 0.995              | 0.511 | 0.511 | 0.510 | 0.509 | 0.508 | 0.508 | 0.507 | 0.506 |
| 1.066              | 0.512 | 0.511 | 0.511 | 0.510 | 0.509 | 0.509 | 0.508 | 0.507 |
| 1.138              | 0.513 | 0.512 | 0.512 | 0.511 | 0.510 | 0.509 | 0.509 | 0.508 |

changes in the availability variations compared to all other systems in the manufacturing plant. In this research, only the critical system was discussed for the development of the optimal and better maintenance management system for the industry. Due to the abnormal availability changes that occur in these two systems as compared to the others, the simulation of availability analysis on system B and system D at the start of this study is displayed. We already applied similar ideas to all other systems in production processes. (Tables 3 and 4) illustrate random sample parameters for system B in fault conditions, as well as availability

fluctuations. (Figure 3) shows the availability analysis result achieved by evaluating system B with the maintenance parameters and the corresponding to system B fault position ( $x = 1$ ) in the critical part production section. More maintenance is invested in the system as the failure rate increases and the repair rate lowers. This is because the failure rate regulates the deterioration of critical systems in a production facility. As a result, the systems maximum failure rate will hasten the degeneration of the system’s critical components. In this case, maintenance is frequently performed on the equipment, increasing the manufacturing plant’s maintenance investment. The systems other parameters, the repair rate, primarily aids in limiting the amount of the degradation process in the workplace. The deterioration energy of mechanical components is inversely proportional to the repair rate. As a result, the average maintenance spending in the industrial sector to lower the system repair rate is at its highest.

The systems are designed to be available, and they have proven to be availability variations using the Google Drive software application. For system B with faulty conditions, the horizontal axis with the repair rate of system B and the availability of the vertical axis will change. The individual system (system B) failure rate has been denoted in the layers as shown in (Figure 3). These randomly sampled layers also consider the particular system availability variations. Based on the maintenance parameters (the failure rate and the repair rate) variations corresponding the system’s availability profile also varied. The availability variance of system B is depicted graphically in this diagram. In both faulty and ideal positions of the system, this availability prediction analysis profile does not become identical; instead, it abruptly rises and falls. These optimal values highlighted in (Figure 3) are provided in the industrial Internet of Things input signal, along with the maximum defined limit (margin values) and associated maintenance parameter values for continuous monitoring and control activities.

This system is classified as the most critical subsystem type in the specified production system of SMEs due to anomalous availability changes on the graphical representation surface. The maintenance parameters of system B are randomly generated in (Tables 3 and 4). The failure rate of system B was randomly generated (0.020–0.060) in the first row of the table. The repair rate of system B is randomly generated in the first column of the table. The remaining rows and columns (matrices) represent system B availability variations.

(Tables 5 and 6) demonstrate the availability fluctuations of system D under malfunctioning situations. The horizontal



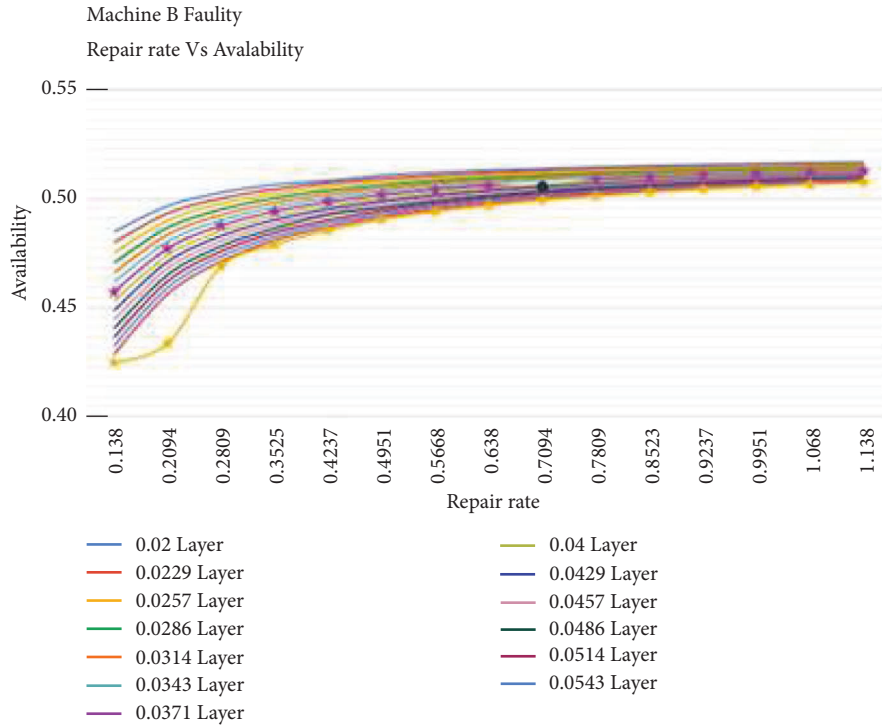


FIGURE 3: Analysis of system B fault position’s availability.

TABLE 5: Variation in fault position as a result of system D availability.

| $\lambda_{D\mu_D}$ | 0.029 | 0.031 | 0.034 | 0.037 | 0.040 | 0.043 | 0.046 |
|--------------------|-------|-------|-------|-------|-------|-------|-------|
| 0.290              | 0.486 | 0.484 | 0.483 | 0.478 | 0.476 | 0.474 | 0.472 |
| 0.361              | 0.493 | 0.489 | 0.487 | 0.485 | 0.483 | 0.481 | 0.480 |
| 0.432              | 0.497 | 0.495 | 0.493 | 0.490 | 0.488 | 0.487 | 0.485 |
| 0.504              | 0.498 | 0.497 | 0.495 | 0.493 | 0.492 | 0.490 | 0.489 |
| 0.575              | 0.501 | 0.499 | 0.497 | 0.496 | 0.495 | 0.493 | 0.492 |
| 0.647              | 0.503 | 0.501 | 0.499 | 0.498 | 0.497 | 0.496 | 0.495 |
| 0.718              | 0.505 | 0.503 | 0.501 | 0.499 | 0.498 | 0.497 | 0.497 |
| 0.0790             | 0.506 | 0.505 | 0.502 | 0.501 | 0.500 | 0.499 | 0.498 |
| 0.861              | 0.507 | 0.505 | 0.503 | 0.502 | 0.501 | 0.500 | 0.499 |
| 0.0932             | 0.508 | 0.507 | 0.504 | 0.503 | 0.502 | 0.501 | 0.501 |
| 1.004              | 0.508 | 0.507 | 0.505 | 0.504 | 0.503 | 0.502 | 0.502 |
| 1.075              | 0.509 | 0.508 | 0.505 | 0.505 | 0.504 | 0.503 | 0.503 |
| 1.147              | 0.508 | 0.508 | 0.506 | 0.505 | 0.505 | 0.504 | 0.504 |
| 1.218              | 0.508 | 0.507 | 0.506 | 0.506 | 0.505 | 0.505 | 0.505 |
| 1.290              | 0.509 | 0.509 | 0.507 | 0.507 | 0.506 | 0.506 | 0.506 |

TABLE 6: Variation in fault position as a result of system D’s availability.

| $\lambda_{D\mu_D}$ | 0.051 | 0.054 | 0.057 | 0.060 | 0.063 | 0.066 | 0.069 |
|--------------------|-------|-------|-------|-------|-------|-------|-------|
| 0.290              | 0.467 | 0.465 | 0.463 | 0.461 | 0.459 | 0.457 | 0.456 |
| 0.361              | 0.476 | 0.474 | 0.472 | 0.472 | 0.469 | 0.467 | 0.465 |
| 0.432              | 0.482 | 0.480 | 0.479 | 0.477 | 0.476 | 0.474 | 0.473 |
| 0.504              | 0.486 | 0.485 | 0.484 | 0.483 | 0.481 | 0.480 | 0.478 |
| 0.575              | 0.490 | 0.489 | 0.489 | 0.487 | 0.485 | 0.484 | 0.493 |
| 0.647              | 0.492 | 0.491 | 0.490 | 0.489 | 0.488 | 0.487 | 0.486 |
| 0.718              | 0.495 | 0.494 | 0.494 | 0.494 | 0.492 | 0.490 | 0.489 |
| 0.790              | 0.496 | 0.495 | 0.495 | 0.495 | 0.494 | 0.492 | 0.491 |
| 0.861              | 0.498 | 0.497 | 0.496 | 0.496 | 0.495 | 0.494 | 0.493 |
| 0.932              | 0.499 | 0.498 | 0.498 | 0.497 | 0.496 | 0.495 | 0.494 |
| 1.004              | 0.500 | 0.499 | 0.499 | 0.498 | 0.497 | 0.497 | 0.496 |
| 1.075              | 0.501 | 0.500 | 0.500 | 0.499 | 0.498 | 0.498 | 0.497 |
| 1.147              | 0.502 | 0.501 | 0.501 | 0.500 | 0.499 | 0.499 | 0.498 |
| 1.218              | 0.504 | 0.502 | 0.502 | 0.501 | 0.500 | 0.499 | 0.499 |
| 1.290              | 0.505 | 0.504 | 0.503 | 0.503 | 0.502 | 0.502 | 0.500 |

axis with which system D has a repair rate will change depending on system D defective conditions. The availability fluctuations of system D are depicted graphically in this diagram. In the defective conditions of the system, this availability analysis profile does not become consistent but rather jumps up and down. These optimal values highlighted in (Figure 4) are provided in the industrial Internet of Things, the maximum defined range (margin values), and associated maintenance parameter values for continuous monitoring and control operations.

This system D is also designated as the second significant subsystem of the specified production system of SMEs due to anomalous availability variations in the graphical

representation profile. Tables 5 and 6 show the maintenance parameters of system D that were chosen at random. The first row of the table explained system D failure rate, which was produced at random (0.029–0.069). System D repair rate is randomly generated in the first column of that table. The appropriate availability variations of system D is denoted by the next row and column (matrices).

### 6. Discussion

The Markov decision model process and MATLAB R2021 Ra software are used to assess variations in critical automobile part manufacturing system availability in this analytical

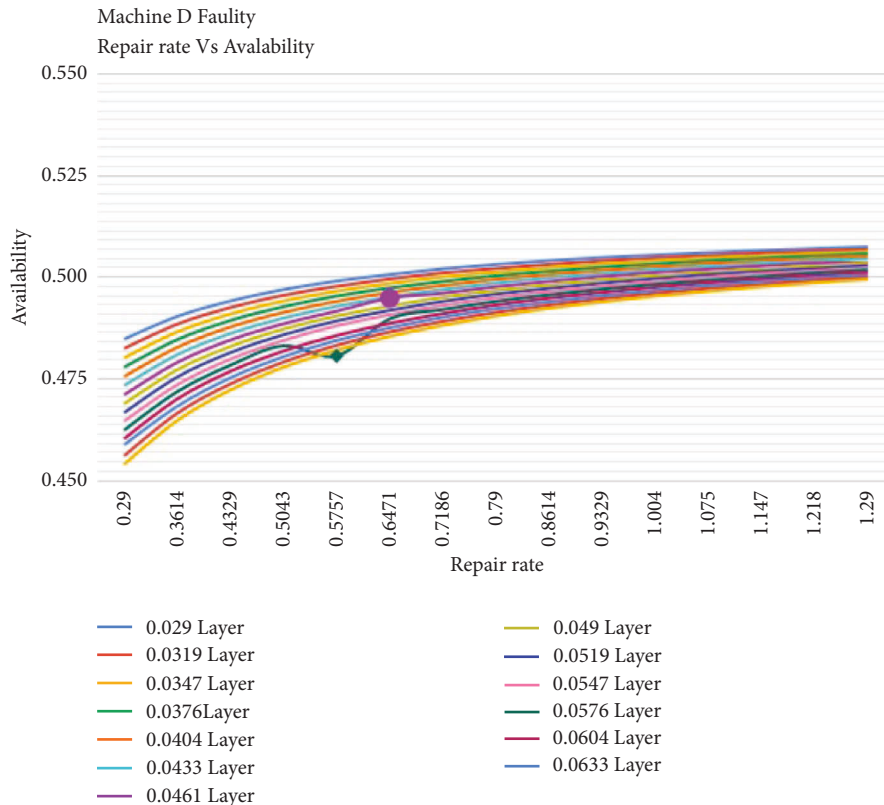


FIGURE 4: Analysis of system D fault position's availability.

study. We will adopt a better and optimum maintenance management system with effective maintenance manpower allocation in the industry based on this providing an optimal solution to the maintenance parameters (the failure rate and the repair rate). Only the availability analysis of the urea synthesis systems at the fertilizer factory was discussed in [17], which proposed prioritizing maintenance planning based on the equipment's maximum availability. Similarly, the application of the Markov decision model technique is used to analyze the complete brewery industry's operation and identify only the most essential subsystem in the operating plant based on availability variation results [20]. However, in this study, they combined the Markov decision model with MATLAB software and new Industry 4.0 technologies such as industrial Internet of Things and Internet communication techniques to develop a novel approach. The manufacturing plant's critical equipment has been identified based on maintenance parameter fluctuations. The smart continuous monitoring and controlling method were being used to organize the PM's autonomous planning and scheduling process in SMEs. Finally, they analyzed the research outcomes and produced a real-time implementation of the autonomous PM planning and scheduling process based on the autonomous framework of the optimal decision-making process of the PM activity depicted in (Figure 5). Because these systems are classified as the most critical subsystems in the overall production system, the repair rate of system B and system D has a huge variation based on that depiction. (Figure 5) shows a graphic

representation of the system repair rates in comparison. Through this availability analysis and repair rate analysis results, all the manufacturing systems are prioritized by the ranking order of the maximum availability such as systems B, D, C, A, D, CD, and AB. The given manufacturing system's performance has improved as a result of the proposed autonomous PM with an optimal decision-making process, as well as no production delays or unexpected system downtime. (Figure 5) depicts the best solution for analyzing the repair rate of a given critical part manufacturing plant in SMEs. The names of the systems on the horizontal and vertical axes are the individual systems repair rates. The projected system repair rate will grow dramatically compared to the present values of the specified working environment in SMEs, achieving the maximum availability of the shop floor's critical subsystems.

The proposed optimal maintenance management approaches have been compared with existing traditional maintenance management approaches in the industry. In the traditional preventive maintenance management system, generally, the yearly scheduled maintenance data and time of the individual machine have been fixed randomly. Based on that scheduled date and time that machine has been stopped for preventive maintenance actions if that machine is in a working or failed state. They do not consider that actual conditions blindly stopped the production and do the preventive maintenance activity. Once completed the preventive maintenance action, the machine is restored to working condition and starts production operations in the

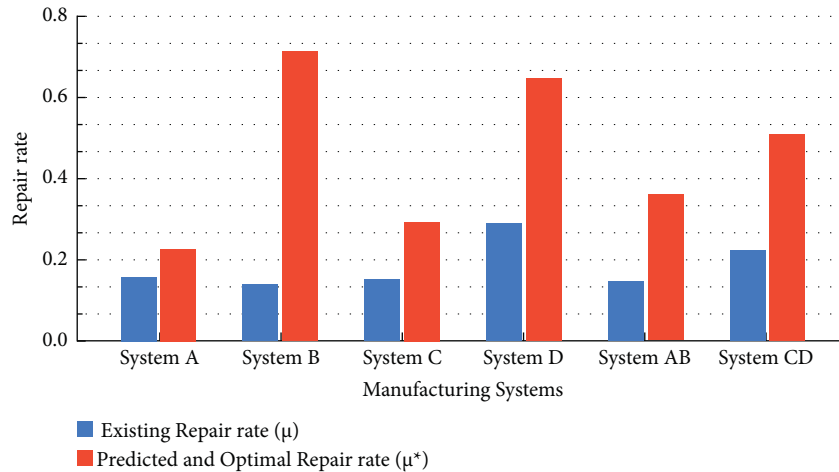


FIGURE 5: An analysis of system repair rates.

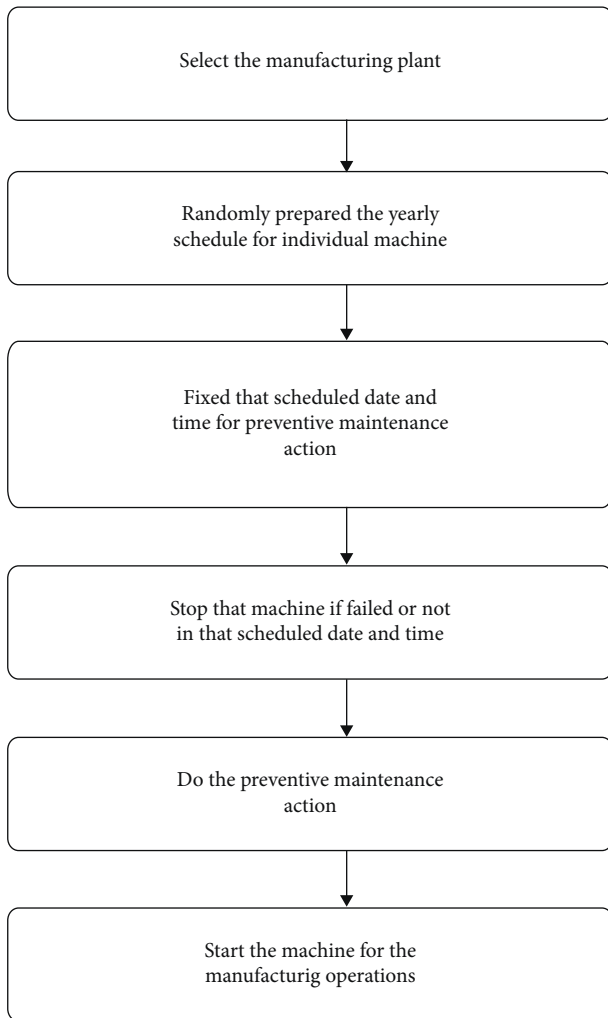


FIGURE 6: Existing preventive maintenance approach in the industry.

manufacturing industry. The flow process of the traditional or existing preventive maintenance activity is shown in (Figure 6).

In the proposed preventive maintenance approach, before the preparation of the scheduled date and time of the preventive maintenance activity of the machines, the performance of the individual machine in the manufacturing plant is analyzed by measuring the availability of the individual machine through the application of mathematical modeling. Based on that mathematical analysis results and the availability variations of the individual machines, the individual machines are categorized as the most critical, critical, and least critical states as per the availability variation of the machines. Once all the machines concerning the maximum and minimum availability of the machine are prioritized, the scheduled date and time have been prepared and fixed the preventive maintenance activity as of date. Through this proposed approach outcome, the downtime of the machine has been minimized and maximized production in the industry. The proposed optimal preventive maintenance approaches are illustrated in (Figure 7). Then the predictive maintenance model has been discussed in (Figure 8), in that situation IIoT sensors are affixed to the machine for the continuous monitoring and data gathering process. A detailed description of the predictive maintenance activity has been described in the implications and implementation sections.

### 7. Managerial Implications

Since availability analysis results in these systems are classified as the most critical subsystems in the overall production system, the repair rate of system B and system D has a huge variation based on that depiction. The given manufacturing system performance has improved as a result of the proposed autonomous maintenance with an optimal decision-making method, with no production delays or unexpected system downtime. Figure 9 illustrated the detailed workflow of this proposed autonomous maintenance management approach in SMEs. In that situation, the activities are classified into four categories such as OP (optimizations), CM (continuous monitoring), DA (data analysis), and IS (information sharing). OP: initially the

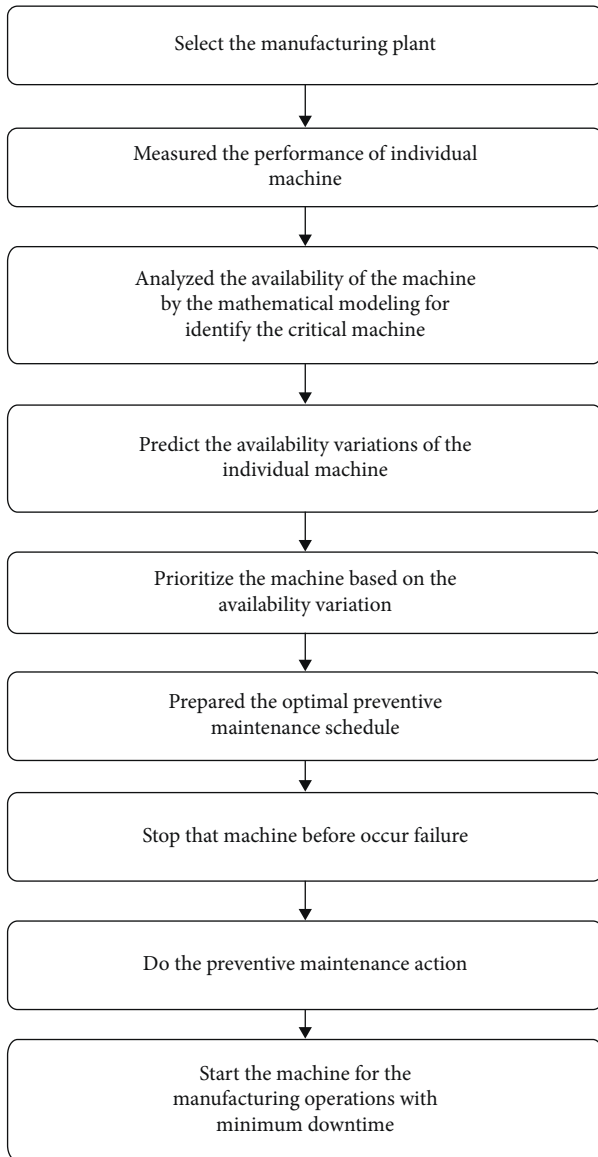


FIGURE 7: Proposed preventive maintenance approach in the industry.

maintenance parameters have been collected from the shop floor area. Next, those real-time maintenance data are analyzed for measuring the availability variations of the individual systems. Finally, the optimal maintenance parameters of the given manufacturing systems are predicted for achieving the maximum availability of the given manufacturing system. It has been described in the previous section. CM: in that situation, predicted optimal maintenance parameters are fed into the input control signal of the IIoT for continuous monitoring of the real-time behavioral changes of that particular critical system in the shop floor area. DA: in this section, the real-time monitored data has been collected from the IIoT sensors. Next those data are analyzed based on our standard constraints such as optimal region, acceptable region, and abnormal region. If those analyzed results achieved the acceptable state, they will be

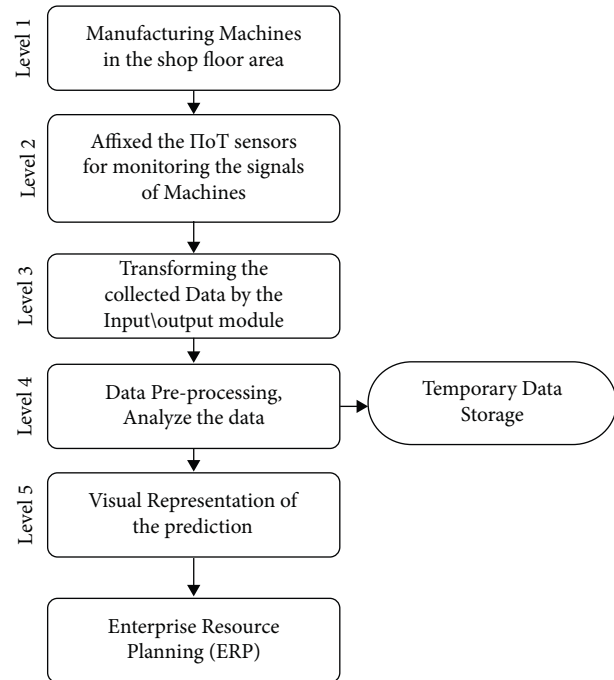


FIGURE 8: Data flow and level of implementation of an optimal maintenance management system.

stored in the temporary storage devices or else the outcomes belong to the abnormal state will proceed for the next activity. IS: in that condition, the up normal state of the systems data has been collected from the previous actions. Based on our constraints behavioral changes and abnormal condition information that are shared with the concerned responsible persons in the working environment for triggering the optimal decision-making of the maintenance management system in SMEs. As a result of this proposed approach scheduling, the effective maintenance workforce in SMEs is used for achieving the maximum productivity of the shop floor area. Using mathematical analysis (Markov decision model) and MATLAB R2019a software, the critical automobile part production plant has assessed and determined a suitable and optimal availability solution for the maintenance planning and scheduling process in the industry. Solutions for predicting the variation limits of each system's optimal maintenance parameters (the repair rate and the failure rate) are supplied based on this research to achieve maximum availability of the industry's critical part production systems. The optimal availability margin in the automobile component production facility is created based on the relevant optimal maintenance parameters of the critical subsystems. These maintenance parameter margin values are included in the IIoT input values for essential subsystems in the industry. Through the smart man-system communication process in the industry, this IIoT is utilized for routine monitoring of the behavior of the critical subsystem, regulating the abrupt failure and downtime of the critical subsystem during manufacturing processes. ICT is being used to achieve autonomous human-system communications in the maintenance sector, as well as to improve

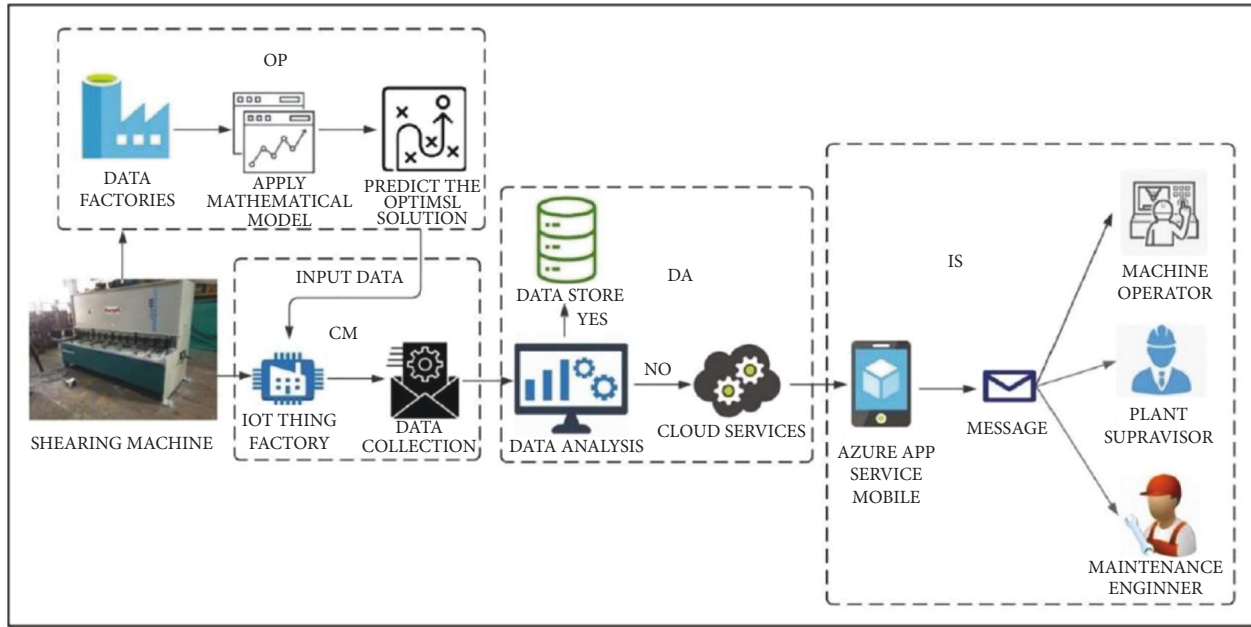


FIGURE 9: The autonomous maintenance management system framework of SMEs.

the availability of critical subsystems in SMEs’ work environments [35, 36]. As a result, IIoT is utilized to track the critical part of manufacturing systems ongoing behavior changes on the shop floor. It was determined to give an input control signal with the best failure rate discovered by the analyzer for this reason. As a result, the availability and reliability of critical subsystems are determined by the maintenance parameter.

### 8. Implementation

This proposed optimal maintenance management systems architecture has been implemented through the following level of the activities in the industry: (1) Physical level: The real-time case study of the manufacturing plant consists of the various machines as discussed in the manufacturing model description (Machine A-Machine D) for producing the cross-member part. These machines are selected as the physical level of the implementation of the optimal maintenance management system. (2) Monitoring and data gathering level: All the machines in the manufacturing plant are affixed to the infrared sensors. The connected sensors have been continuously monitoring the behavioral changes of the individual machine and shared that data into the analysis sections by application of the transferring model. (3) Input/Output connectivity level: The data aquations are used for transferring the sensor signals into the binary or digital values through the application of the computer addition of the input/output module. Every machine has an individual input/output pin for details data collection. (4) Data analysis and temporary storage level: In this section, the data analysis and storage process has been initiated through the application of data mining technologies attached to the input/output panel of the computer. (5) Visual presentation and information sharing level: Finally, the analyzed result has

been displayed in the shop floor area through the visual representations for the optimal decision-making of the maintenance management system in the industry. The data flow process of this optimal maintenance management system is shown in (Figure 8).

Those optimal decision-making activities information is shared with the responsible person through SMS, or e-mail with the help of Wi-Fi/Bluetooth connectivity. The optimal decision-making, autonomous maintenance, and service requesting purpose ICT technologies have been introduced in this proposed architecture (Figure 9). In the IS activity, the continuous maintenance parameters have been monitored and predicted the abnormal range of the maintenance parameters through the initialization of the IIoT sensors in the individual machines. The real-time monitored data have been shared in the data analysis sections with the help of the Bluetooth or wireless connectivity model. The collected data have been analyzed based on the standard and optimal maintenance parameters of the individual machine in the production plant. If any deviations of the maintenance parameters have been identified through the binary classification 0 for an acceptable or optimal range of the maintenance parameter variations, that data have been stored in the temporary storage device for the future analysis of the machine availability and 1 for an abnormal range of the maintenance parameters. That actual data of the abnormal range of the maintenance parameters will share with the concerned persons (machine operator, production supervisor, and maintenance engineer) with the application of the ICT addition of the Bluetooth and wireless mode such as sent a mail, messages, blurring the indication lamp, and triggering the alarm.

System B is recognized as the most critical system in the manufacturing process of SMEs due to abrupt changes in its

TABLE 7: Optimal maintenance parameters of systems.

| Systems      | Existing repair rate<br>( $\mu$ ) | Predicted optimal repair rate<br>( $\mu^*$ ) |
|--------------|-----------------------------------|--|
| System A     | 0.158                             | 0.2294                                       |
| System B     | 0.138                             | 0.7094                                       |
| System C     | 0.150                             | 0.2929                                       |
| System D     | 0.290                             | 0.6471                                       |
| System AB    | 0.144                             | 0.3583                                       |
| System<br>CD | 0.224                             | 0.5097                                       |

availability. (Figure 3) depicts the availability variance of system B with highlighted optimal points. Based on the stored data, determine the optimal availability (0.5056) and corresponding failure rate (0.0371), and repair rate (0.7094). Using the formula for calculating the failure rate in the previous section (data processing), determine the optimal interval time for system B's PM function. It also applies to other critical subsystems of the SMEs' critical automobile part production plant. In the critical part production system of SMEs, (Table 7) provides the optimal maintenance parameter values of individual systems. These projected individual subsystem maintenance parameters will produce maximum SMEs availability and optimal PM maintenance performance.

## 9. Conclusion

In the SME automobile spare parts manufacturing industry, this study article addresses the optimal maintenance strategy for the best and optimal decision-making process of the critical parts manufacturing plant. The provided automobile spare part manufacturing systems are simply classed as the least and most critical production systems in the sheet metal forming industry based on the availability analysis results. The PM process's suitable and optimal time interval (maintenance schedule) was predicted based on the industry's maximum availability of critical part manufacturing systems. The optimal repair rate of the manufacturing system in the industry was used to achieve maximum availability of critical part production systems in SME, as evidenced by system repair rate analysis. Through this outcome of research, the most critical subsystem in the manufacturing environment of SMEs is identified and isolated and then initiated the prioritized maintenance management activities in the shop floor area such as systems B, D, C, A, CD, and AB.

Finally, using this proposed autonomous, the optimal PM management system framework with the latest Industry 4.0 technology based on this research, it is possible to achieve greater productivity, customer satisfaction, and profitability in SMEs by computerizing PM planning and scheduling functions and improving the performance and effectiveness of the maintenance workforce, as demonstrated by the real-time industrial implementation. The primary study's assessment of age-based maintenance action through the previous year's maintenance record data is among the

study's limitations. Only a proposal was made for the smart and optimal PM planning and scheduling process in SMEs.

This proposed PM framework will be used in future research to integrate the PdM activities of critical subsystems and their components in the industry with the best decision support system for PdM activities in SMEs. The current smart maintenance management strategy enables SME manufacturing industries to plan and schedule conditional maintenance to achieve optimal maintenance.

## Notations

- A, B, C, D: Systems in good operating order.  
a, b, c, d: Systems in state of maintenance  
 $a^*$ ,  $b^*$ ,  $c^*$ , Systems should be repaired.  
 $d^*$ :  
M: Systems (A, B, C, D, AB, and CD)  
A: Shearing operation system.  
B: Cropping operation system  
C: Piercing operation system.  
D: Bending operation system  
 $\lambda_M$ : The rate of system failure  
 $\mu_M$ : The rate of system repair  
 $\phi_M$ : The rate of system transition.  
 $\eta_M$ : The rate of system PM  
 $x$ : Constant (0 for ideal and 1 for faulty)  
 $P_0(t)$ : All system's probability functions are in their original conditions  
 $P_i(t)$ : The corresponding system probability functions are being serviced. ( $i = 1, 3, 5, 7, 9, 11$ )  
 $P_j(t)$ : The corresponding system probability functions are being repaired. ( $j = 2, 4, 6, 8, 10, 12$ ).

## Data Availability

The data used to support the findings of this study are included within the article.

## Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this research article.

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