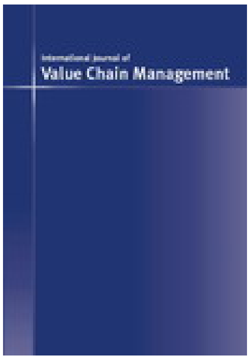

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Industry 4.0: smart preventive maintenance with optimal planning and scheduling process of the SMEs

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Abstract: In the modern world, small and medium scale manufacturing industries face a lot of challenges to achieve the reliability, availability, and safety as important performance attributes of the shop floor. In which planning and scheduling of preventive maintenance activities are considered to be a major issue in SMEs. This study is to propose the optimal framework of the preventive maintenance (PM) planning and scheduling process in SMEs. The optimal maintenance parameters (failure rate and repair rate), availability variations of the systems have been predicted through the utilisation of the Markov birth-death approach. To overcome the drawbacks associated with the existing optimal PM plan, a new approach is proposed in this study to develop an optimal preventive maintenance plan for electronic actuating switch manufacturers through the digital ecosystem. This proposed method integrates manufacturing subsystem failure into smart digital ecosystems and also to estimate the actual remaining useful life of the machines.

Keywords: small and medium sized enterprises; preventive maintenance; Markov birth-death process; remaining useful life; optimal planning and scheduling.

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1 Introduction

Manufacturing and production industries have grown rapidly around the world due to the expansion of the human population. Nowadays, the manufacturers start implementing a smart and effective maintenance process to increase productivity, employee performance, customer satisfaction and reduce machine idle time, production delay in the manufacturing industry's shop floor area and it becomes the need of the hour (Hajej et al., 2018). The RUL of critical machine components is one of the most important functions in maintenance management systems of the manufacturing industry. Sudden failures of the complex system and its subsidiaries in the maintenance system of the manufacturing plant led to capital investment and unexpected production loss of the industry (Tang et al., 2019). Therefore, it is to introduce a planned and PM process to reduce capital investment, sudden failure, and idle time of critical machine components in the industry. Sudden failures of complex systems and subsystems are very critical in the process because these failures can lead to the destruction of the entire sequence of manufacturing processes in the industry. Effective PM planning and scheduling strategies lead to the reduction of unplanned workforce and production delays in the industry. Achieving maximum reliability of complex systems is of paramount importance in the recent competitive production environment. Optimal reliability and availability of complex systems can be streamlined by scheduling the working hours of maintenance employees.

There are several definitions of maintenance, which are defined as restoring or retaining machine components to their original condition by performing routine testing and operation in the industry. It is divided into two types as PM and corrective maintenance (CM). Of these, PM is further classified into two categories: conditional Based Maintenance (CBM) and age-based maintenance (ABM). This study is mainly focused on the ABM function of the complex systems in the manufacturing plant (Wang et al., 2019). Availability simulation of complex systems is organised by making the Markov birth-death approach. Mathematical models of complex systems in the production process are obtained with the transition state diagram of a particular manufacturing system with the utilisation of first-order differential equations. These equations are solved by using MATLAB R2019a software to identify the optimal solution of a given availability simulation (Velmurugan et al. 2019a). The real-time prediction of the RUL of the manufacturing subsystems has not been considered during the current maintenance management system for SMEs, but this factor is the most critical in the day-to-day operations for the smooth running of EAS manufacturing process machines. Upon reviewing the literature and applying Industry 4.0 applications to SMEs, the reliability availability maintainability (RAM) might be improved by integrating Industry 4.0 technology. Therefore, this study is relevant to measuring the RAM of PM in the EAS process of sensor manufacturing.

This study considers three types of conditioning machines as follows,

a the original or raw level machines are ready to run the state

b The machine has minor faults, but it is in an operating condition which is called under maintenance conditions

c the machine has a big fault, and it cannot work by the so-called failed condition machines.

Using IIoT is used to constantly monitor the complex system behaviours, usage, and downtime of the manufacturing machines. The ICT is one of the autonomous human-machine communications that helps in monitoring a complex system. This simulation of research mainly proposes new optimal and autonomous PM planning and scheduling of complex systems in the manufacturing plant. The objective of this study is to measure the availability variation of the individual machine for identifying the critical subsystems in the EAS process in the manufacturing industry. The continuous monitoring systems in the critical subsystem are to develop the optimal PM planning and scheduling process in the industry. And it helps to organise the suitable and effective workforce allocation of maintenance teams in the given manufacturing plant based on this research prediction. The Markov birth-death process is a widely used technique for the RAM evaluations of the machines and their components. This study analyses the performance of the individual machines based on the availability changes. The importance of this study is to explore the optimal PM planning and scheduling framework in the shop floor area. To improve the productivity of the manufacturing plant through the effective workforce allocation of the maintenance department in the industry. The smart and optimal schedule increases the efficiency of the manufacturing machines, maintenance team, productivity, and customer satisfaction in small and medium-sized enterprises.

The rest of this paper is organised as follows: The review of literature of this study and research gap is discussed in Section 2. In Section 3, the problem description of the research study and production process is presented. In Section 4, the smart PM strategy of the production system, mathematical modelling is detailed. The numerical results, Discussion application, proposed simulation of the complex system in SMEs, are described in Section 5. Finally, in Section 6, the conclusion, limitations, and future scope of this availability simulation research of critical part production systems in SMEs are given.

2 Literature review

Initially, to expand our survey of the literature, we have included recent research work on the product functionality and PM upgrades of the sensor manufacturing industry. In many production areas, a variety of strategies have proven to be effective. Through an overview of large numbers of maintenance management with Markov birth-death process related research studies, the various factors and challenges, applications considered to optimal maintenance management systems in SMEs, and the research gap have been illustrated in the following sections.

The imperfect effect of the IoT-enabled diagnostic system of service and maintenance architecture has been described (Sun et al., 2021). Analysed the maintenance and service provider decision-process through the strategic quenching model, predictive maintenance tools for developing the optimal maintenance policy with a cost-effective decision-making process. Zhao et al. (2021) investigated the maintenance management system of the nuclear power plant. They have predicted the degradation of the nuclear power plant systems through the utilisation of Bayesian network, hidden Markov and sequential algorithm models for organising the suitable and optimal maintenance management system in the power plant. Lee et al. (2021) examined e-maintenance capability with continuous monitoring of semiconductor fabrication equipment. Based on their findings, IoT-enabled web-controlled maintenance and service action prediction benefits the semiconductor industry. This prediction has initiated the IoT-enabled web-controlled maintenance and service action in the semiconductor manufacturing domain for the better maintenance management system. A smart optimal PM plan with the IIoT enabled continuous machine health monitoring system has been organised with the utilisation of the machine learning algorithm and logistic regression analysis approach

(Velmurugan et al. 2021a). Tewari and Malik (2016) have reviewed numerous reviews of the literature on the performance modelling, reliability, availability, maintenance, and economic analysis of key subsidiaries in coal-fired thermal power plants. In another research that followed, the forecast issues of a manufacturing plant based on quality issues were discussed (Hajej et al., 2018) and then analysed the production, failure, and defect rates and organised the industry to improve maintenance operations with minimum maintenance cost policy. Velmurugan et al. (2021b) investigated the performance analysis of the rubber industry. The performance of the individual machines has been analysed and predicted as the most critical subsystem in the manufacturing process by the application of the Markov birth-death process, MATLAB R2019a software. Similarly, Kim et al. (2015) investigated the optimal planning and scheduling process of the maintenance management system of the mainstream purification method. It has been proposed through the application of the conventional dynamic programming model and Markov birth-death process analysis. Wang et al. (2019) describe the opportunistic maintenance (OM) policy of two series systems in turbines, which analyse two different units of maintenance policies using an ABM policy and compare it with other maintenance methods and advise on optimal maintenance action of the Semi-Markov decision process (SMDP) wind turbine. It used this to predict critical components and proposed a new framework for optimal CM, PM, and OM policy. Not only that but Tang et al. (2019) explained the state-of-the-art RUL prediction that would degrade the complex engineering system, analysing the aircraft and space vehicle system with different dynamic operating conditions through the unique-time Markov chain process and the SMDP and the new RUL forecast model and critical engineering system optimal maintenance planning has been proposed. In another research, Hajej et al. (2020) developed an optimal integrated production and maintenance policy for a wind turbine. They analyse the relationship between wind turbine production rate and failure rate through the cost model of wind models and describe a large-scale, maintenance strategy that is optimally integrated with energy consumption for multiple mechanical systems. A sensitivity analysis was conducted by Wang et al. (2020) to reduce maintenance costs and guarantee maximum availability by using a dynamic and imperfect PM model of wind turbines. Akbarinasaji et al. (2020) described the analysis of software usage problems such as development of bug message during the online software used. They have predicted and prioritised the errors, and resolving the bug message in the software usage problem in the firebox software by the utilisation of the partially observable Markov decision process, partially observable Monte Carlo planning approaches. Wang and Miao (2021) Formulated the optimal PM model of the balanced system through the application of the SMDP. The challenges in the implementation of the IoT-enabled condition-based maintenance management system has been described by Ingemarsdotter et al. (2021). They have analysed the effects of applications and challenges in the integration of the CBM with IoT technology. The optimal maintenance scheduling process of the chemical plant and natural gas regulating, and metering stations has been proposed through the application of the dynamic Bayesian network model with the influence diagrams and Markov model (BahooToroody et al., 2019). Table 1 has described the recently published and most relevant research articles overviews in detail.

Table 1 Critical overview of the most relevant research articles

Authors	*Tools and techniques*	*Results*
(Kumar et al, 2015; Wakiru et al., 2019)	Net present value method, semi Markov decision process	Developed the optimal maintenance management systems in the thermal power plant
(Taheriyoun and Moradinejad, 2015; Smit et al., 2019)	Fault tree, availability analysis with semi Markov approach	Measured the availability, performance of the water treatment plant operations
(Yousefi et al., 2020: Yu et al., 2019)	Markov decision process, value iteration algorithms	Predict the efficient route planning of the mobile agent and vacant taxi in the china down
(Liu et al., 2021; Traini et al., 2020)	Machine learning, petri net model	Developed a framework design of the condition-based maintenance of the equipment with real-time monitoring and measuring the RUL of critical machines
(Wang et al., 2019; Kumar et al., 2014)	SMDP, decision support system, availability analysis	Identified the critical components in the wind turbine, brewery plant and organise the optimal maintenance management systems.
(Zhang et al., 2021)	SMDP	The optimal maintenance decision-making process of the modular multilevel converter has been proposed.
(Aggarwal et al., 2015; Jain and Rani, 2013)	Markov birth-death process, dynamic programing model	Organised the optimal maintenance policy with the maximum availability of the fertiliser plant operations and others
(Velmurugan et al., 2019b)	Markov birth-death process, MATLAB software	Identified the critical subsystems in the rubber industry and developed the new model check sheet to achieve the optimal PM process in the industry.
(De Saporta and Zhang, 2013; Garg et al., 2010)	Piecewise-deterministic markov process, risk management and analysis technique	Developed the predictive maintenance management model of the heated Holdup Tank in the thermal power plant. To develop the optimal maintenance management system with the maximum availability of crank-gas production systems
(Tewari et al., 2012, Kadiyan et al., 2012)	Genetic algorithm, Markov decision process	Organised the optimal maintenance policy based on the identification of the critical subsystem in the industry
(Sánchez-Herguedas et al., 2021; Guiras et al., 2019)	SMDP, Z transform equations and heuristic algorithm	Developed the optimal decision support tool for the cost-effective maintenance program. and analysed the two-stage maintenance plan of the assembly section in the industry
(Pitchipoo et al., 2013)	Artificial neural network	To organise the optimal supplier selection of the production plant
(González-Domínguez et al., 2021a)	Markov model, condition based maintenance model	Obtained the optimal maintenance policy and frequency of the ceramic curved tile roof and measured the degradation of computed tomography equipment

Through the review of recently published research papers show that various mathematical techniques are effectively used to assess the RAM of machines for an optimal PM management system. They are also widely used in high-end original equipment manufacturing, wind farms, mining, ship, and aircraft construction industries.As a result of the literature review, the availability of manufacturing subsystems was not considered in PM planning. Implementing PM through smart ecosystem frameworks in SMEs in Tamil Nādu, India, to achieve optimal decision making. The following three research questions (RQ) were formulated to address the research gaps in this study.

RQ1 Why is the optimal maintenance management system a necessity in SMEs?

RQ2 How to measure the performance of the maintenance workforce in SMEs?

RQ3 How to develop smart and optimal PM management systems in SMEs?

Furthermore, this study analysed a real-time case study on electronic switches and sensors manufacturing industry by utilising the novelty of integrated analysis approaches like Markov decision model, and the latest technologies (Industry 4.0) such as IIoT, ICT. Detailed explanations of this study have been described in the following section.

3 Problem description

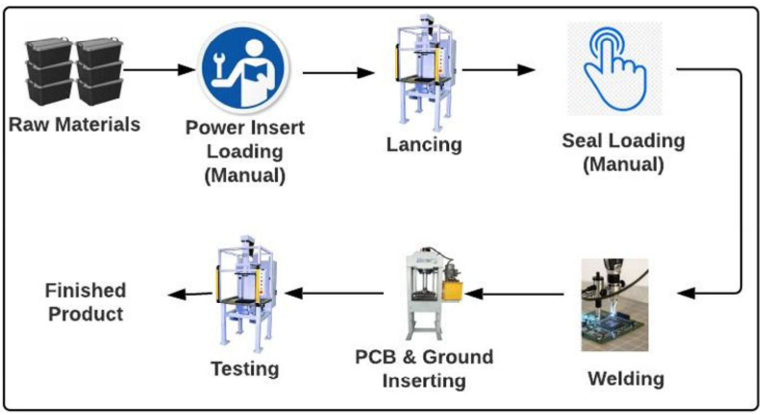
Initially, the assumptions used to create the optimal planning and production model of the PM management system are provided. The production method of the EAS production process is briefly described, and the maintenance issues of this system are discussed. This availability analysis of the maintenance model confirms the following assumptions.

- Initially, each critical systems are in its original state or better (A, B, C, D, AB, and CD).
- The repair and failure rate of each complex system is constant and statistically independent (λ M, μ M) (M = A, B, C, D, AB, and CD)
- Every system that is repaired is considered new.
- Single maintenance team to handle the PM activity of the system.
- Every critical system has three states as original, maintenance, and repair (e.g., A, a, and a*).
- Simultaneous failure of the required systems (AB and CD) is also considered.
- The rate of PM and transition of the critical systems are taken as constant (η_M, ϕ_M = constant).

3.1 Complex product production model

The real-time case study is to investigate the sensors and switch manufacturing industry located in Tamil Nadu, India. They have produced automotive parts for various customers around the world. Which EAS is the most important assembly unit in the industry. These parts are mainly used for automatic control window glass operation in modern vehicles. This EAS has numerous critical child parts, and it is the most critical part production system in the industry. In the critical part production region, the manufacturing flow process involves complex systems within the shop floor area. These production units operate three-shift (working hours) due to high demand from customers. Because of improper PM maintenance planning leads to product delays and production loss. The purpose of this research is to reduce the unnecessary repair time of manufacturing machines through the proposed optimal PM planning and scheduling framework in the industry. This EAS process includes the following sequence of the manufacturing operation in the shop floor area of the SMEs such as power insertion loading, lancing, seal loading, welding, board insertion, and testing. A graphical representation of the sequential production flow process of the EAS part is shown in Figure 1.

Figure 1 Production flow process of the electronic actuating switch (see online version for colours)

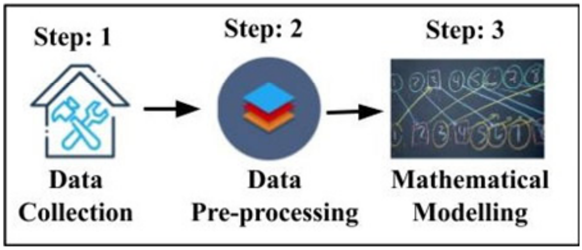


In this production model, four machines are operated during the operation. The service and maintenance policy of each machine depends on the RUL of the critical machine components. The purpose is to create the optimal PM scheduling and planning process of the critical machines in the production plant, which is the forecast of the RUL of the machine components, achieving maximum profit, productivity in the shop floor area of the SMEs. The availability analysis of each production model and the RUL estimation of the machine components are determined in the following sections.

4 Research methodology of smart preventive maintenance strategy

The optimal PM strategy of this research study consists of several sequences of research procedures to achieve the smart PM planning and scheduling process of the given EAS manufacturing plant in the SMEs. The pictorial representation flow process is shown in Figure.2.

Figure 2 Research steps for the smart pm planning and scheduling process in the SMEs (see online version for colours)



4.1 Data collection

The EAS machine maintenance and utility data in 2019 to 2020 of selected complex production systems are collected from the maintenance department based on historical records sheets. A time series of machine running time, optimal time, actual maintenance, production delay time, and PM schedule time has been gathered from the maintenance department of the sensor manufacturing industry for the EAS process. In order to determine the optimal PM plan of SME, the collected data were evaluated through a ranking process by industry experts. The following data were used for performance and availability analysis of the manufacturing subsystem. The manufacturing subsystems such as failure rate, repair rate, and PM rate (shown in Table 2) have been determined to be appropriate to estimate the availability variation as well as the maintenance workforce performance in the EAS manufacturing process in industry.

4.2 Data processing in advance

In Pre-processing data collected related to the availability appropriate analysis of the reliability and availability of the production system in the machine maintenance data are included. The groups of machine data are classified separately for our availability analysis based on the measured individual critical machine repair rate, failure rate, and PM rate using the mathematical expression given in equation (1) and equation (2).

The repair rate (μ) of the individual complex system is defined as the ratio of the total failures (X) that occur on the complex machine to the total maintenance time (Y) of that critical machine in the production plant. The identified critical lancing machine receives 216 failures per year, and the machine maintenance time in the annual production schedule is 5 days per month in the industry. Its measures the repair rate (μ = 0.150) of the lancing machine in the automotive parts manufacturing system. The expression of the repair rate estimate is explained below:

$$\mu = \left(X/Y \right) \Rightarrow \left(\frac{216}{24 \times 5 \times 12} \right) = 0.150 \tag{1}$$

Lansing machine repair rate (μA) = 0.150 failures/hour. Likewise, all the other machine's repair rates are evaluated through the application of equation (1).

The failure rate (λ) of the individual complex system of the production unit is defined as the ratio of the total number of failures (X) occurring on the complex machine, to the total usage time (Z) of that critical machine in the production unit. The Lancing machine receives 216 failures throughout the year, and that machine contributes 24 hours a day and 30 days per month in the production unit measuring the Lansing machine-specific failure rate (λ = 0.025). The mathematical expression of the failure rate calculation is explained below.

$$\lambda = \left(X/_{Y} \right) \Rightarrow \left(\frac{216}{24 \times 30 \times 12} \right) = 0.025 \tag{2}$$

Lancing machine failure rate (λA) = 0.025 failures/hour. Similarly, the other manufacturing machine's failure rates are measured by the utilisation of equation (2). The maintenance parameters of the machine in the manufacturing unit are shown in Table 2.

Table 2 Maintenance parameters of the automotive spare part production unit

Machine	*Total numbers of failures per year (X)*	*Total maintenance time per year (Y) Hrs*	*Total utilisation time per year (Z) Hrs*	*Repair rate (μ) X/Y*	*Failure rate (λ) X/Z*
Machine A	216	1,440	8,640	0.150	0.025
Machine B	120	864	5,760	0.138	0.020
Machine C	84	288	2,880	0.290	0.029
Machine D	228	1,440	8,640	0.158	0.026
Machine AB	168	1,152	7,200	0.145	0.023
Machine CD	156	864	5,760	0.090	0.027

4.3 Mathematical modelling

The transition state diagram of the critical machine is illustrated in Figure 3. Based on this transition state diagram the individual machine consists of three-phase operations (original, reduced capacity, and failure) to generate the first-order differential availability analytical equations of the critical systems in the manufacturing plant. Mathematical equations in availability analytics are generated by using the first-order differential equations (Velmurugan et al., 2019b). The future behaviour of the current critical part production system was finally evaluated through the application of the Markov birth-death approach. In this scenario, all systems of the critical machines consider three states. Original, under maintenance, and failed condition.

The probability function of machines in the critical part production system initially began to shift from a good condition to a low level of maintenance. The mathematical representation of the Markov model equation is given below

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

The probability function of the machines in the critical part production system began to transform from the maintenance stage to the repaired stage. After maintenance and service operation, those production machines are restored to good condition. The mathematical representation of the Markov decision model equation is illustrated below:

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

4.4 Stable position of critical part production model

The production process of the critical part of all systems is steady state. In all these conditions the transition time of all systems is assumed to be zero (through $t = 0$). at equilibrium above equation (3) and equation (4). Finally, we obtain the equilibrium probability equations produced by the critical part production systems (Velmurugan et al., 2019a).

$\frac{d}{dt} \rightarrow 0$ Value available to us, such as $t \rightarrow \infty$

$$\eta_M P_j = \phi_M P_0 \tag{5}$$

$$\mu_M P_j = \eta_M x P_i + \lambda_M P_0 \tag{6}$$

The solves the equations (above 3–4) again and again and the value we get

$$P_i = D_i P_0, P_j = D_j P_0 \tag{7}$$

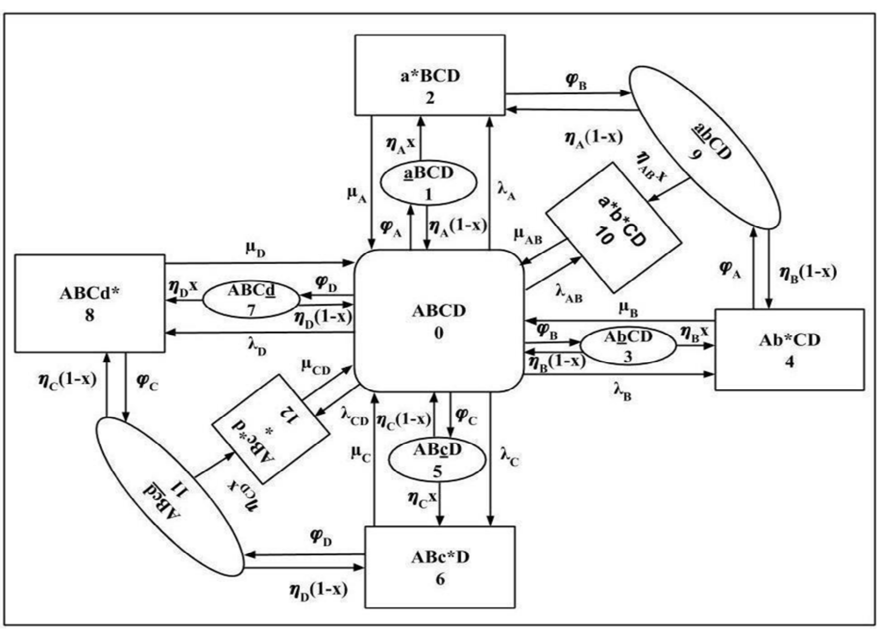
where

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

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

The static-level probability equations of the critical part production systems are obtained and then apply the default state of the above equations. The normalisation level equation is described below as the sum of all the probabilities of the critical part production system is equal to 1.

Figure 3 Transition state diagram of the critical part production system



Using the normalisation position

$$\sum_{i=1}^{11} P_i + \sum_{j=2}^{12} P_j = 1 \tag{8}$$

$$Av = \left(1 + \sum_{i=1}^{11} P_i + \sum_{j=2}^{12} Pj\right) \tag{9}$$

$$A_v = P_0 \tag{10}$$

5 Numerical result of the critical part production system

The numerical values of the individual production machines are used in the above equations to measure the availability changes of the critical part production system in the sensor manufacturing industry. The input numerical values are shown in Table 3. These standard values are used directly for the availability measurement equations with two different conditions, the machines are in the faulty position, and the machines are in the idle position. Thereafter, these values are categorised into higher models with our control limits using MATLAB R2019a software. These randomly generated values are used in equation (9) to predict the optimal and maximum availability of a given EAS manufacturing system in SMEs.

Table 3 Input numeric values for the availability analysis of the system

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

The simulation of availability analysis on machine B and machine C at the beginning of this study is demonstrated due to the abnormal availability changes that occur in these two machines compared to the others. Similarly, these techniques are applied to other machines based on their critical conditions in production systems. Random sample parameters with availability variations of machine B in the fault conditions shown in Tables 4a and 4b. Figure 4 illustrates the result of the availability analysis obtained by considering the machine B with the maintenance parameters and the corresponding to the faulty position of the machine B (x = 1) in the critical part production section. As the failure rate of the machine increases and the repair rate of the machine decreases, more maintenance is invested in the machine. This is because the failure rate controls the decay of critical machines in the EAS manufacturing plant. Thus, the maximum failure rate of the machine will accelerate the deterioration of the critical components in the machine. In this situation, the maintenance machine is often done on the machine, which simultaneously increases the maintenance investment in the manufacturing plant. The other parameter repair rate of the machine mainly contributes to controlling the extent of the degradation process in the work environment. The repair rate is inversely proportional to the degradation energy of the mechanical components. Therefore, the average maintenance investment in the production machine to reduce the repair rate of the machine is maximal.

Table 4a The effect of the availability variation of machine B in the faulty position

μB \ λB	*0.020*	*0.022*	*0.025*	*0.028*	*0.031*	*0.034*	*0.037*	*0.040*
0.138	0.484	0.479	0.475	0.470	0.465	0.461	0.457	0.452
0.209	0.496	0.493	0.490	0.486	0.483	0.480	0.477	0.474
0.280	0.502	0.500	0.497	0.495	0.492	0.490	0.487	0.485
0.352	0.506	0.504	0.502	0.500	0.498	0.496	0.494	0.492
0.423	0.508	0.507	0.505	0.503	0.502	0.500	0.498	0.496
0.495	0.510	0.509	0.507	0.506	0.504	0.503	0.501	0.500
0.566	0.512	0.510	0.509	0.508	0.506	0.505	0.504	0.502
0.638	0.513	0.511	0.510	0.509	0.508	0.507	0.506	0.504
0.709	0.513	0.512	0.511	0.510	0.509	0.508	0.507	0.506
0.780	0.514	0.513	0.512	0.511	0.510	0.509	0.508	0.507
0.852	0.515	0.514	0.513	0.512	0.511	0.510	0.509	0.509
0.923	0.515	0.514	0.514	0.513	0.512	0.511	0.510	0.510
0.995	0.516	0.515	0.514	0.513	0.513	0.512	0.511	0.510
1,066	0.516	0.515	0.515	0.514	0.513	0.512	0.512	0.511
1,138	0.516	0.516	0.515	0.514	0.514	0.513	0.512	0.512

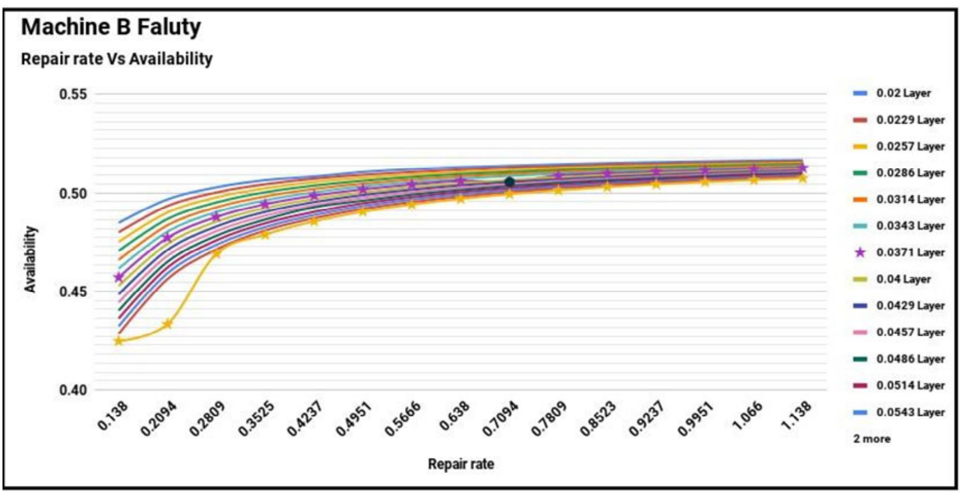
Table 4b Effect of availability variation of machine B in fault position

μB \ λB	*0.040*	*0.042*	*0.045*	*0.048*	*0.051*	*0.054*	*0.057*	*0.060*
0.138	0.452	0.448	0.444	0.440	0.436	0.432	0.428	0.424
0.209	0.474	0.471	0.468	0.465	0.462	0.459	0.456	0.433
0.280	0.485	0.482	0.480	0.478	0.475	0.473	0.471	0.469
0.352	0.492	0.490	0.488	0.486	0.484	0.482	0.480	0.478
0.423	0.496	0.495	0.493	0.492	0.490	0.488	0.487	0.485
0.495	0.500	0.498	0.497	0.496	0.494	0.493	0.491	0.490
0.566	0.502	0.501	0.500	0.499	0.497	0.596	0.495	0.494
0.638	0.504	0.503	0.502	0.501	0.500	0.499	0.498	0.497
0.709	0.506	0.505	0.504	0.503	0.502	0.501	0.500	0.499
0.780	0.507	0.506	0.506	0.505	0.504	0.503	0.502	0.501
0.852	0.509	0.508	0.507	0.506	0.505	0.504	0.503	0.503
0.923	0.510	0.509	0.508	0.507	0.506	0.505	0.505	0.504
0.995	0.510	0.510	0.509	0.508	0.507	0.507	0.506	0.505
1,066	0.511	0.510	0.510	0.509	0.508	0.508	0.507	0.506
1,138	0.512	0.511	0.510	0.510	0.509	0.508	0.508	0.507

The machines are built to be available and have proven to be availability variants with the graph through the Google Drive application. The horizontal axis with the repair rate of machine B and the availability vertical axis will vary for machine B with faulty conditions. This graphical representation shows the availability variance of machine B. This availability analysis profile does not become identical, it is abruptly up and down in both faulty and idle positions of the machine. Those optimal values (highlighted in Figure 4) are given in the input signal of the IIoT with the maximum defined limit (margin values) and the associated maintenance parameter values for continuous monitoring and control operations.

Due to the abnormal availability changes on the graphical representation surface, this machine is classified as the most critical subsystems type in the given EAS production system of the SMEs. Tables 4a and 4b consist of the randomly generated maintenance parameters of machine B. The first row of that table denoted the randomly generated (0.020–0.060) failure rate of machine B. The first column of that table consists of the randomly generated repair rate of machine B. The remaining rows and columns (Matrices) show the corresponding availability variations of machine B.

Figure 4 Availability analysis of machine B in faulty condition (see online version for colours)



The availability variations of machine C with faulty conditions are shown in Tables 5a and 5b. The horizontal axis with which the machine C has a repair rate, and the availability vertical axis will vary with the faulty conditions of the machine C. This graphical representation shows the availability variations of the machine C. This availability analysis profile does not become uniform, it is abruptly up and down in the faulty conditions of the machine. Those optimal values (highlighted in Figure 5) are given in the input signal of the industrial web contents of the maximum defined range (margin values) and the associated parameter values for continuous monitoring and control operations.

Due to abnormal availability changes in the graphical representation profile, this machine C is also classified as the second important subsystem of the given EAS production system of the SMEs. Tables 5a and 5b consist of the randomly selected maintenance parameters of machine C. The first row of that table explained the randomly generated (0.029–0.069) failure rate of machine C. The first column of that table consists of the randomly generated repair rate of machine C. The next row and column (Matrices) are denoted the corresponding availability variations of machine C.

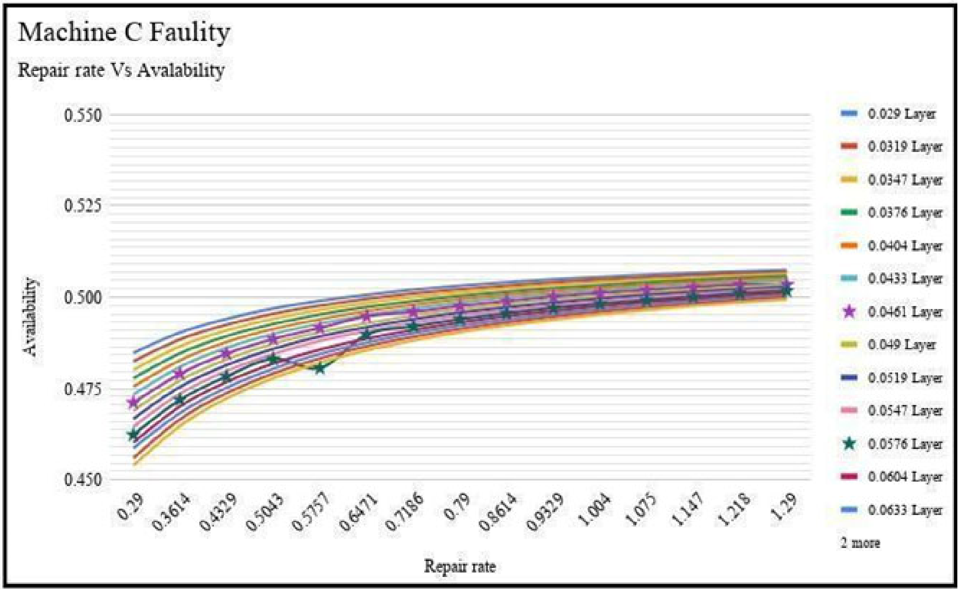
Table 5a Effect of availability variation of machine C in fault position

μC \ λC	*0.029*	*0.031*	*0.034*	*0.037*	*0.040*	*0.043*	*0.046*
0.290	0.484	0.482	0.480	0.477	0.475	0.473	0.471
0.361	0.490	0.488	0.486	0.484	0.482	0.480	0.479
0.432	0.494	0.492	0.490	0.489	0.487	0.486	0.484
0.504	0.496	0.495	0.494	0.492	0.491	0.489	0.488
0.575	0.499	0.497	0.496	0.495	0.494	0.492	0.491
0.647	0.500	0.499	0.498	0.497	0.496	0.495	0.494
0.718	0.502	0.501	0.500	0.498	0.497	0.496	0.496
0.0790	0.503	0.502	0.501	0.500	0.499	0.498	0.497
0.861	0.504	0.503	0.502	0.501	0.500	0.499	0.498
0.0932	0.504	0.504	0.503	0.502	0.501	0.500	0.500
1,004	0.505	0.504	0.504	0.503	0.502	0.501	0.501
1,075	0.506	0.505	0.504	0.504	0.503	0.502	0.501
1,147	0.506	0.505	0.505	0.504	0.504	0.503	0.502
1,218	0.507	0.506	0.505	0.505	0.504	0.504	0.503
1,290	0.507	0.506	0.506	0.505	0.505	0.504	0.503

Table 5b The effect of the availability variation of machine C with faulty position

μC \ λC	*0.051*	*0.054*	*0.057*	*0.060*	*0.063*	*0.066*	*0.069*
0.290	0.466	0.464	0.462	0.460	0.458	0.456	0.453
0.361	0.475	0.473	0.471	0.470	0.468	0.466	0.464
0.432	0.481	0.479	0.478	0.476	0.475	0.473	0.472
0.504	0.485	0.484	0.483	0.481	0.480	0.479	0.477
0.575	0.489	0.488	0.488	0.485	0.484	0.483	0.492
0.647	0.491	0.490	0.489	0.488	0.487	0.486	0.485
0.718	0.494	0.493	0.492	0.491	0.490	0.489	0.488
0.0790	0.495	0.494	0.494	0.493	0.492	0.491	0.490
0.861	0.497	0.496	0.495	0.494	0.493	0.493	0.492
0.0932	0.498	0.497	0.497	0.496	0.495	0.494	0.493
1,004	0.499	0.498	0.498	0.497	0.496	0.496	0.495
1,075	0.500	0.499	0.499	0.498	0.497	0.497	0.496
1,147	0.501	0.500	0.500	0.499	0.498	0.498	0.497
1,218	0.502	0.501	0.501	0.500	0.499	0.499	0.498
1,290	0.502	0.502	0.501	0.501	0.500	0.500	0.499

Figure 5 Availability analysis of machine C fault position



5.1 Discussion

In this study, EAS production machines' availability changes are measured with the help of MATLAB software and the Markov birth-death process. Based on this proposed optimal solution of the maintenance parameters (failure rate and repair rate) to implement a better and optimal maintenance management system with an effective maintenance workforce allocation in the industry. From this availability analysis results, the availability prediction of individual manufacturing subsystems are analysed through mathematical modelling. The availability variation of the subsystems is classified as the most critical manufacturing subsystem based on the minimum or sudden reduced availability conditions. In the sensor manufacturing industry, the availability of the actuator switch manufacturing subsystems (machine B and machine C) consists of abrupt changes and reduction, due to which these two manufacturing subsystems have been considered as the most critical among all other subsystems. The similar results were supported by the study of Aggarwal et al. (2015) in the fertiliser manufacturing industry. In the present study, the effectiveness of the maintenance workforce was also measured through the availability variations of the individual manufacturing subsystem. The optimal allocations, prioritisation of the maintenance workforce in the maintenance department has been achieved based on the availability analysis and it is evident by the similar results by Kumar et al. (2014) through the proposed smart digital ecosystem framework in wind turbine manufacturing industry. But in this study, particularly introduced the novel approach of integrated analysis techniques like Markov birth-death process with the addition of the MATLAB software, recent Industry 4.0 technology such as IIoT and ICT. The critical machines of the manufacturing plant have been identified based on the maintenance parameters variations as well as the availability of the individual system Then applied with the smart continuous monitoring and controlling a process to organise the autonomous planning and scheduling process of the PM in the SMEs. Finally, developed the real-time implementation of smart PM planning and scheduling process based on the smart framework of the PM planning and scheduling process as shown in Figure 6. The outcome analysis results of this study was compared with repair rates of the individual machines, and it is graphically shown in Figure 7. From that representation, the repair rate of machine B and machine C has a large variation, due to the availability reduction in which these machines are classified as the most critical subsystems in the entire manufacturing system of the SMEs. After introducing this proposed smart PM planning and scheduling process framework, the given manufacturing system, maintenance workforce may increase their performance and effectiveness without production delay and unexpected downtime of the machines in the SMEs.

5.2 Applications and simulation of smart maintenance system

In this analysis study, the EAS part production plant has analysed and identified a suitable, optimal availability solution of the PM planning and scheduling process in the industry using mathematical analysis (Markov birth-death) with MATLAB software. Based on this research, solutions for estimating variation limits of individual machine optimal maintenance parameters (repair rate and failure rate) to achieve maximum availability of EAS production system sensor manufacturing industry. Creating the optimal availability margin based on the relevant optimal maintenance parameters of the critical subsystems in the EAS part manufacturing plant. Those margin values of the maintenance parameters are given in the input values of IIoT for individual critical subsystems in the sensor manufacturing industry. This IIoT is used for routine monitoring of the behaviour of the critical subsystem, controlling the sudden failure and downtime of the critical subsystem during the manufacturing operations through the smart man-machine communication process in the industry. ICT is one of the best tools for maintenance and planning of system communication applied to achieve autonomous human-machine communications to create a consistent workforce in the maintenance sector and to increase the availability of the critical subsystem in the work environment of SMEs (Zhang et al., 2020; Devi et al., 2020; Kumar et al., 2021).

As such, IIoT is used to monitor the continuous behavioural changes of the critical part manufacturing machines in the shop floor area. For this purpose, it was decided to provide an input control signal with the optimal failure rate detected by the analyser. Thus, the maintenance parameter determines the maximum availability and reliability of important subsystems. This IIoT device transfers the monitored data into the storage unit then specific critical machine behaviour of real-time data is analysed based on the stored data with limited (optimal) maximum critical availability subsystem concerning the value of machine maintenance parameters. If that data signal meets our barrier of being stored on a temporary data storage device, the machine will continue to run. Otherwise, infringed data signals are designed to share timely and accurate information (SMS operator, plant supervisor, and maintenance engineer) through short message service (SMS), tower light signal, and audio alarm. ICT with wireless network and cloud computing technology the graphical demonstrations of the proposed Smart PM architecture are shown in Figure 6.

Figure 6 The framework of smart PM planning and scheduling process (see online version for colours)

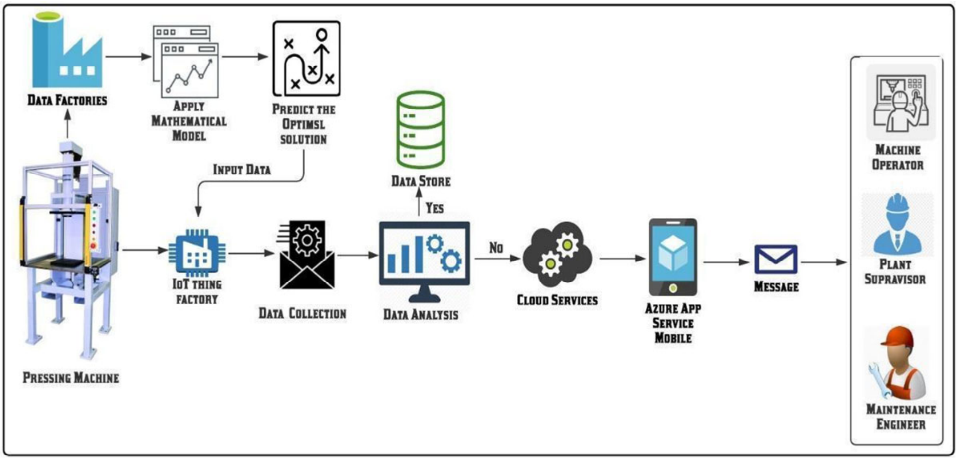
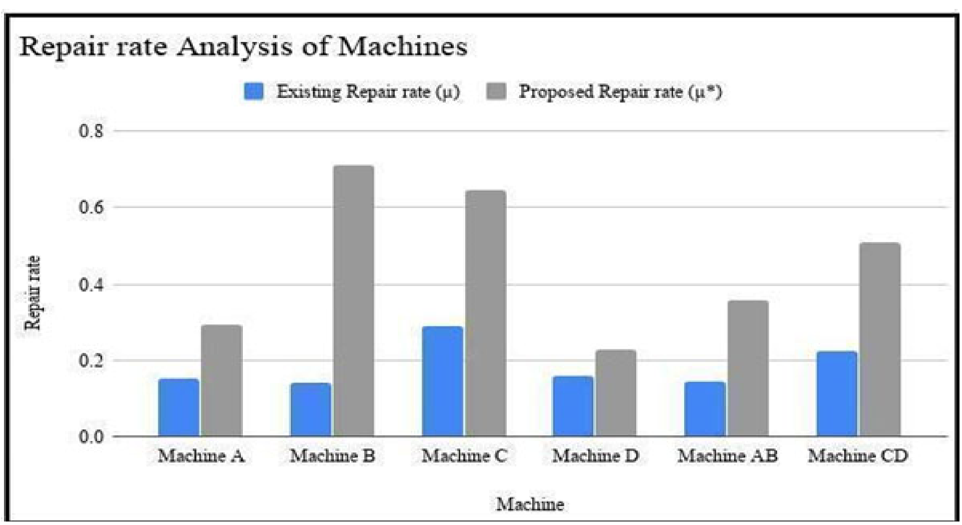


Table 6 Optimal maintenance parameters of machines.

Machine	*Existing repair rate (μ)*	*Predicted*
Optimal repair rate (μ*)		
Machine A	0.150	0.2929
Machine B	0.138	0.7094
Machine C	0.290	0.6471
Machine D	0.158	0.2294
Machine AB	0.144	0.3583
Machine CD	0.224	0.5097

Figure 7 Repair rate analysis of machines (see online version for colours)



The availability variance of machine B with highlighted optimal points has shown in Figure 4. On selecting the optimal availability (0.5056) and the associated failure rate (0.0371) based on the stored data. The optimal interval time of the PM function of Machine B using the formula for measuring the failure rate in the data processing was identified. Similarly, it applies to other important subsystems of the EAS part production plant in the SMEs. Table 6 shows the optimal maintenance parameter values of individual machines in the critical part production system of SMEs. These predicted maintenance parameters of individual subsystems will lead to the maximum availability of SMEs and optimal PM maintenance performance.

The optimal solution for the repair rate analysis of the specific EAS part manufacturing plant in SMEs is shown in Figure 7. The name of the machines on the horizontal axis and the vertical axis is the repair rates of the respective machines. In the machine repair rate analysis, the proposed repair rate will increase drastically compared to the existing values of the given working environment in the SMEs that achieve the maximum availability of the critical subsystems of the shop floor.

6 Conclusions

This study considers the PM policy for the optimal planning and scheduling process of the automotive spare parts manufacturing plant in the sensor manufacturing industry. Based on the availability results, the given automotive part production systems are easily classified as the least and most important production systems in the industry. The suitable and optimal time interval (maintenance schedule) of the PM process was predicted considering the maximum availability of the critical part manufacturing systems in the sensor manufacturing industry. The maximum availability of critical systems in the manufacturing plant was achieved by doing the PM with the optimal repair rate of the manufacturing system in the industry, so this has been demonstrated by machine repair rate analysis. Finally, this proposed computerising PM planning and scheduling functions may improve the performance of the manufacturing system, effectiveness of the maintenance workforce in the SME. Using the proposed autonomous, optimal PM framework with the ICT, it is possible to achieve greater productivity, customer satisfaction, profitability and it is proven in this industrial implementation. This study has few limitations, the ABM action through the previous year maintenance record data of PM planning and scheduling process was only considered. In future research, this proposed PM framework will utilise the PdM activity of critical sub-sub systems in the industry with the optimal decision-making process of SMEs operations. The optimal maintenance achieved through the current smart maintenance strategy enables conditional maintenance planning and scheduling of SMEs.

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Notations

A, B, C, D The working condition of the machines.

a, b, c, d Under Maintenance condition of the machines.

a *, b *, c *, d * Repair condition of machines

A Lansing machine.

B Welding machine.

C Pressing machine.

D Testing machine.

λ_M Machine failure rate. (M = A, B, C, D, AB and CD)

μ_M Machine repair rate.

ϕ_M Machine transition rate.

η_M PM rate of the machine.

x Constant (0 for idle and 1 for faulty)

$P_0(t)$ Probability function of all machines is in original condition.

$P_i(t)$ Probability functions of the respective machines are under maintenance. (i = 1,…3, 5, 7, 9, 11)

$P_j(t)$ Probability functions of the respective machines are under repair.

j 2, 4, 6, 8, 10, 12).