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A Multi-State Model for Reliability Analysis of Metal Sheet Manufacturing Process using Artificial Neural Network Technique

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ABSTRACT

A manufacturing system is governed by its various processes upon which its efficiency is dependent. Since, failure results in considerable losses, many manufacturing systems have certain redundancies for some processes. These redundancies cause the system to work under different efficiency states called multi-state elements. In this paper various processes of metal sheet manufacturing unit have been categorized as subsystems to determine the multi-state probabilities of its different efficiency states. Artificial Neural Network Technique (ANN) has been used to estimate the change in these multi-state probabilities over time. The ANN has also been used to estimate variation in upstate and downstate probabilities of the system for a particular-time period. The results have been used to determine variation in profit over time for the system.

Keywords: Artificial neural network, downstate, metal sheet manufacturing, reliability, state transition, upstate

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INTRODUCTION

A well-established industrial process is designed to provide the best quality product within optimum cost. However, these processes are susceptible to failures due to various reasons. Most of the industrial processes are designed to accommodate parallel redundancy with reduced functionality of plant so as to minimize the losses during corrective maintenance of the process. This leads to the whole system being working under different efficiency states. These states are referred to as multi-state elements (MSE) and such a system is known as multi-state system (MSS). The conventional methods for reliability analysis assume a system to be a binary-state system (BSS) i.e. it has only two states – perfectly working state and failed state (Rausand & Høyland, 2004). However, most of the real-world systems are complex and they fall under the classification of MSS as they undergo many levels of degradation states between perfectly working state and a failed state (Natvig, 2011). Thus studying industrial processes, like metal sheet manufacturing process, as an MSS rather than a BSS is useful for practical assessment of its profitability and reliability. Furthermore, predicting the probability of these multi-states is essential to make many important decisions from selecting appropriate maintenance strategy to other measures for reducing downtime probability. The study on reliability assessment of MSS has its history since mid 1970s wherein, the fundamental concepts were introduced (Murchland, 1975) and Boolean methods extension technique was used for reliability modeling of such systems (Barlow & Wu, 1978). Since then researchers have studied various methods for reliability modeling of MSS including Multiple Valued Logic (MLV) (Zaitseva & Levashenko, 2017) universal generating function (UGF), Markov and Semi-Markov Processes (Lisnianski & Levitin, 2003; Lisnianski et al., 2010). While MLV is an extension of Boolean method, in UGF the distribution of performance output of system is obtained on the basis of performance distribution of its elements. Markov and Semi-Markov process modeling analyze the reliability of MSS under assumption that failure and repair times are exponentially distributed (Lisnianski et al., 2012; Li et al., 2018b; Liu et al., 2014; Fang et al., 2016). Researchers have also used a combination of Markov Model with dynamic Bayesian Network for reliability assessment of MSS (Alyson & Aparna, 2007; Li et al., 2018a).

The modeling technique of MSS mentioned above has its own usages and limitations. These techniques have certain pre-assumptions regarding statistical distributions of various states, failure and repair rates and are generally used to ascertain the steady state behavior of the system. However, a metal sheet manufacturing plant is a high demand industrial process as it is required to be in continuous working state for most of its useful life to meet the requirements of industry. Due to which it has a tendency to reach its deteriorating phase quite rapidly and failures no longer follow any particular distribution. This makes the relationship between each of the parameters viz., failure rate, repair rate and states with respect to time more complex. Additionally, to keep the system in profitably working state, the repairs, replacements and maintenance have to be optimized quite frequently duly considering those complexities. Artificial Neural Network (ANN) Models are capable to learn and model such complex real-life systems. On the basis of observed industrial data, the ANN can not only model but also predict the future states by understanding the levels of adjustment in the weights assigned (in this case failure and repair rates) to its neurons.

Furthermore, no prior assumption, especially regarding the distributions of failure/repair rates is required to model a system using ANN. Now-a-days ANN modeling computations are convenient and yield more precise estimates due to availability of a variety of software and high processing speeds of modern computers. Due to these reasons ANN has wide range of applications in many fields including that of reliability (Karunanithi et al., 1992) and, in recent times, ANN models are gaining popularity for reliability estimation of systems (Hurtado & Alvarez, 2001; Sharma et al., 2016; Reshid et al., 2017; Bhargava & Handa, 2018; Chandra et al., 2019).

Evaluating Steady State Probabilities are useful for evaluating reliability of a system for a considerably long period of time. However, an industrial system, like metal-sheet manufacturing plant, which is under high demand and susceptible to deterioration in short span of time, short term state probability analysis is preferred to steady state probabilities.

Considering above-mentioned factors, the objective of this study is to understand short-term behavior of various state probabilities of metal sheet manufacturing plant, using ANN model, in its two phases, (i) “Useful life” during which failure rates of its sub-systems remain constant with time and (ii) “Wear-out phase” or “deterioration period” during which failure rates of its sub-systems start to increase with time. The effect of these variations on profitability of system, under two specific types of preventive maintenance has also been discussed.

Metal sheet production Industry has a global market size of 265 billion US dollars with expected increase of 5% per year (Grand View Research, 2020). It has application in important industrial sectors like automobile, railways, construction and machinery (Kozaki et al., 2017). The workers generally work in an eight to ten hour shift, with machines being run for 24 X 7, to meet this ever-increasing demand. As per report of World Steel Association, India is second highest producer of raw steel after China (Angel, 2019). In the financial year 2019, India produced 82.4 million tonnes of finished steel product (Bhati, 2019). Due to ever increasing demand of metal sheet the evaluation of reliability of metal sheet manufacturing process becomes equally important.

The metal sheet manufacturing process consists of different processes and these processes can be put under the following operations (Bhattacharyya, 1997; Kalpakjian & Schmid, 2001; de Sousa, 2016):

a. Cutting, in which various techniques like roll forming, shearing, blanking, fine blanking and punching are used to cut metal sheets as per requirement

b. Bending, in which various techniques like, V-shaped, edge bending, Shearing etc. are used to bend the metal as per requirement

c. Drawing, in which trimming and slitting of sheets are done to make convex or concave shapes

d. Dye and Coloring of final product

MATERIALS AND METHODS

System Configuration

Considering the processes as subsystems for reliability estimation, the series-parallel configuration for successful operation of metal sheet manufacturing is given in the form of a block diagram given in Figure 1 and its state transition diagram is given in Figure 2.

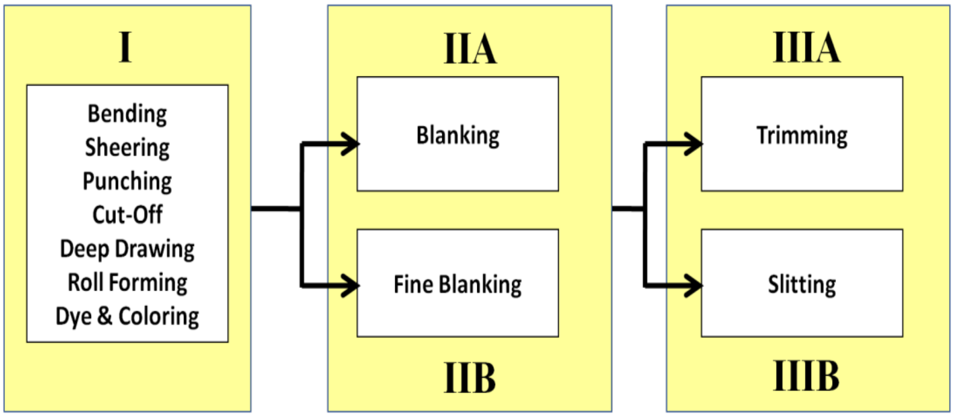


Figure 1. Block Diagram for Successful Operation of Metal Sheet Manufacturing Plant

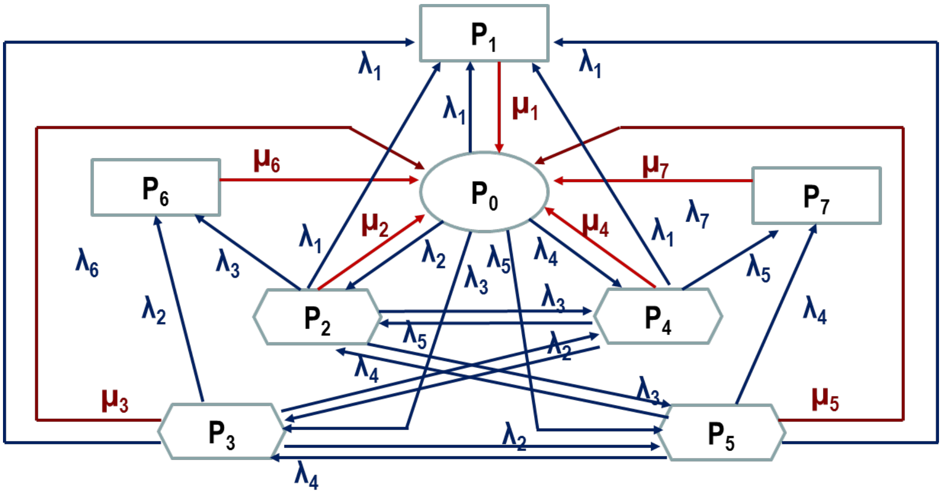


Figure 2. State Transition Diagram of the System

The subsystems are:

I = Bending, Sheering, Punching, Cut-Off, Deep Drawing, Roll Forming, Dye & Coloring

IIA= Blanking

IIB = Fine Blanking

IIIA = Trimming

IIIB = Slitting

The state probabilities are

P_0 = All subsystems are in working state

P_1 = Subsystem I fails and system fails

P_2 = Subsystem IIA fails and system works with degraded efficiency

P_3 = Subsystem IIB fails and system works with degraded efficiency

P_4 = Subsystem IIIA fails and system works with degraded efficiency

P_5 = Subsystem IIIB fails and system works with degraded efficiency

P_6 = Subsystem IIA &IIB fails and system fails

P_7 = Subsystem IIIA & IIIB fails and system fails

Notations

λ_1 = Failure Rate of subsystem I

λ_2 = Failure Rate of subsystem IIA

λ_3 = Failure Rate of subsystem IIB

λ_4 = Failure Rate of subsystem IIIA

λ_5 = Failure Rate of subsystem IIIB

λ_6 = Failure Rate of subsystem IIA & IIB

λ_7 = Failure Rate of subsystem IIIA & IIIB

μ_1 = Repair Rate of subsystem I

μ_2 = Repair Rate of subsystem IIB

μ_3 = Repair Rate of subsystem IIB

μ_4 = Repair Rate of subsystem IIIA

μ_5 = Repair Rate of subsystem IIIB

μ_6 = Repair Rate of subsystem IIA & IIB

μ_7 = Repair Rate of subsystem IIIA & IIIB

Assumptions

The following assumptions have been associated with this model

i. Initially, the state probabilities are known

ii. The states of all processes are statistically independent

iii. Failure of each process follows arbitrary failure time

iv. Repair facility is available and Repair Rates are constant

v. Maintenance Strategy adopted is Corrective Type, unless specified otherwise

vi. No defect is caused in the sheets during shifting from one process to the other

Formulation of Artificial Neural Network (ANN) Model

When the metal sheet manufacturing system is in downstate, due to failure in any one of the processes, the losses incurred are high (Tang et al., 2007). Due to this reason the availability of repair facility and formulating appropriate maintenance strategy becomes equally important.

ANN Model of the System

The ANN is designed to mimic functioning of human brain. Input data and target output data is fed into the ANN model. The model trains itself, by reducing error, after certain number of trials (called epochs) to give the best estimates for output data.

The proposed ANN model contains an input layer, a hidden layer and output layer.

Input Layer. Input are defined as Equation 1

$$Xi = Pi(t), i = 1, \dots 7 \quad [1]$$

Neurons. The numbers of neurons are equal to number of states given in transition diagram given in Figure 4. The neural weights of each state are assigned according to the failure or repair rates of that particular state as per details given below:

The weights of neural network are (Equation 2-23):

$$W_{01} = W_{21} = W_{31} = W_{41} = W_{51} = \lambda_1 \Delta t \quad [2]$$

$$W_{02} = W_{34} = W_{35} = W_{36} = \lambda_2 \Delta t \quad [3]$$

$$W_{03} = W_{24} = W_{26} = \lambda_3 \Delta t \quad [4]$$

$$W_{04} = W_{52} = W_{53} = W_{57} = \lambda_4 \Delta t \quad [5]$$

$$W_{05} = W_{25} = W_{42} = W_{43} = W_{47} = \lambda_5 \Delta t \quad [6]$$

$$W_{06} = \lambda_6 \Delta t \quad [7]$$

$$W_{07} = \lambda_7 \Delta t \quad [8]$$

$$W_{10} = \mu_1 \Delta t \quad [9]$$

$$W_{20} = \mu_2 \Delta t \quad [10]$$

$$W_{30} = \mu_3 \Delta t \quad [11]$$

$$W_{40} = \mu_4 \Delta t \quad [12]$$

$$W_{50} = \mu_5 \Delta t \quad [13]$$

$$W_{60} = \mu_6 \Delta t \quad [14]$$

$$W_{70} = \mu_7 \Delta t \quad [15]$$

$$W_{00} = 1 - W_{01} - W_{02} - W_{03} - W_{04} - W_{05} - W_{06} - W_{07} \quad [16]$$

$$W_{11} = 1 - W_{10} \quad [17]$$

$$W_{22} = 1 - W_{21} - W_{24} - W_{25} - W_{26} - W_{20} \quad [18]$$

$$W_{33} = 1 - W_{31} - W_{34} - W_{35} - W_{36} - W_{30} \quad [19]$$

$$W_{44} = 1 - W_{41} - W_{42} - W_{43} - W_{47} - W_{40} \quad [20]$$

$$W_{55} = 1 - W_{51} - W_{52} - W_{53} - W_{57} - W_{50} \quad [21]$$

$$W_{66} = 1 - W_{60} \quad [22]$$
$$W_{77} = 1 - W_{70} \quad [23]$$

Hidden Layer. Contains activation function defined by Equation 24

$$f(Z = Z) \quad [24]$$

Output Layer. Outputs are represented by Equation 25

$$Yi = Pi(t + \Delta t) \quad \textit{where } i = 1\text{-}7 \quad [25]$$

ANN (Figure 3) is given by Equation 26 and 27

$$Y(j((= f\ \Sigma WijXi + bj \quad i, j = 0 \text{ to } 7, \quad [26]$$

$$bj \text{ is bias, } j = 0 \text{ to } 7 \quad [27]$$

with linear activation function as defined in Equation 24.

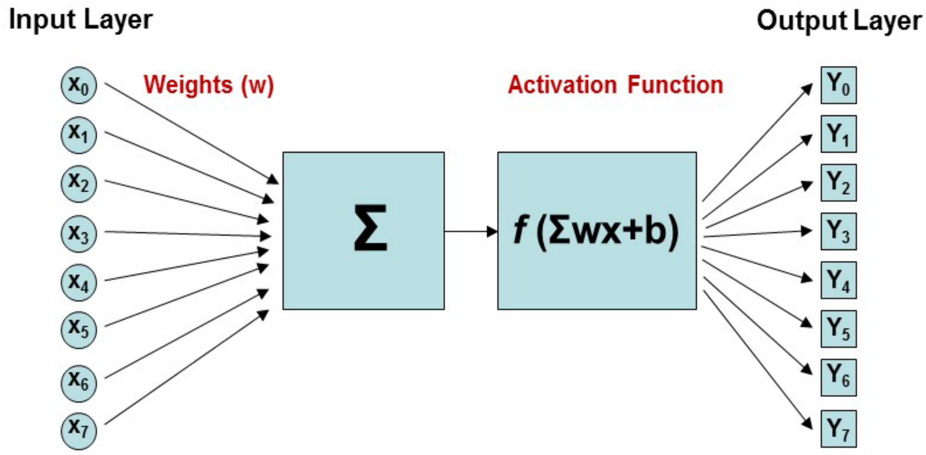


Figure 3. The Artificial Neural Network (ANN) Model of System

Solving ANN model, the outputs are given by substituting the values of Equation 2-23 in Equation 26 and using Equation 24 and 27 the outputs are given by Equation 28-35

$$Y_0 = W_{00}X_0 + W_{10}X_1 + W_{20}X_2 + W_{30}X_3 + W_{40}X_4 + W_{50}X_5 + W_{60}X_6 + W_{70}X_7 + b_0 \quad [28]$$
$$Y_1 = W_{01}X_0 + W_{11}X_1 + W_{21}X_2 + W_{31}X_3 + W_{41}X_4 + W_{51}X_5 + b_1 \quad [29]$$
$$Y_2 = W_{02}X_0 + W_{22}X_2 + W_{42}X_4 + W_{52}X_5 + b_2 \quad [30]$$
$$Y_3 = W_{03}X_0 + W_{33}X_3 + W_{43}X_4 + W_{53}X_5 + b_3 \quad [31]$$
$$Y_4 = W_{04}X_0 + W_{24}X_2 + W_{34}X_3 + W_{44}X_4 + b_4 \quad [32]$$
$$Y_5 = W_{05}X_0 + W_{25}X_2 + W_{35}X_3 + W_{55}X_5 + b_5 \quad [33]$$
$$Y_6 = W_{06}X_0 + W_{26}X_2 + W_{36}X_3 + W_{66}X_6 + b_6 \quad [34]$$
$$Y_7 = W_{07}X_0 + W_{47}X_4 + W_{57}X_5 + W_{77}X_7 + b_7 \quad [35]$$

The Upstate and Downstate probabilities are given by Equation 36 and 37

$$P_{upstate} = Y_0 + Y_2 + Y_3 + Y_4 + Y_5 \quad [36]$$

$$P_{downstate} = Y_1 + Y_6 + Y_7 \quad [37]$$

In the above-mentioned model, State Probabilities at time 't' (input of ANN) are defined by Equation 1 and variations in those State Probabilities at time increment $(t + \Delta t)$ (output of ANN) are defined by Equation 25 and 26.

RESULTS AND DISCUSSION

Estimated Variations in State Probabilities, with Time

A system, at a particular time t, time factor being in months, has been considered for numerical computations and comparison of state probabilities. It has been assumed that the system has been under continuous operation, the initial state probabilities of the system are taken as given in Table 1. The Repair Rates (constant over time) are as given in Table 2. While Table 3 represents the two cases of Failure Rates, (i) Useful life of system when failure rate is constant and (ii) Wear-out phase of system when failure rate becomes time dependent. In case (i) constant failure rate of each subsystem is defined by its respective exponentially distributed survival function and in case (ii) time-dependent failure rate of each subsystem is defined by its respective Weibull distributed survival function and failure rate is defined as Equation 38:

$$\lambda(t) = \beta t^{\beta-1}/\eta^{\beta} \quad [38]$$

The shape parameters (β) and scale parameters (η) of time dependent failure rates of each subsystems at time, t = 0 have been taken to match the initial failure rates of respective subsystems assuming constant failure rates.

Table 1

Initial State Probabilities of Subsystems (Input Values for ANN)

$P_0(t) = X_0$	$P_1(t) = X_1$	$P_2(t) = X_2$	$P_3(t) = X_3$	$P_4(t) = X_4$	$P_5(t) = X_5$	$P_6(t) = X_6$	$P_7(t) = X_7$
0.45	0.05	0.1	0.1	0.1	0.1	0.05	0.05

Table 2

Repair Rates of Subsystems

Repair Rates (per month)	μ_1	μ_2	μ_3	μ_4	μ_5	μ_6	μ_7
Values	0.02	0.01	0.01	0.01	0.01	0.02	0.02

Table 3
Failure Rates of Subsystems Assuming Time-Dependent Failure Rates v/s Constant Failure Rates

Failure Rates (per month)	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7
Scale Parameter	0.75	1.65	2.36	3	5	3.5	1.36
Shape Parameter	2	2	2	2	2	2	2
Failure Rate at t=0 (Weibull)	0.0497	0.0102	0.005	0.0031	0.0011	0.0022	0.015
Failure Rate (Constant)	0.05	0.01	0.005	0.003	0.001	0.02	0.015

In the proposed ANN model, bias is a constant added to activation function to shift the estimated values state probabilities to closer to observed state probabilities. But since in this numerical computation observed state probabilities have not been taken hence assuming b_j =0.

Applying ANN to the input state probabilities given in Table 1, taking time as a factor of months and $\Delta t = 10\ hours = 0.014\ month$ and taking weights as combination of repair and failure rates as mentioned in Equation 2-23, the estimated changes in State Probabilities of subsystems with time increment of 10 hours, computed using ANN model outputs given in Equation 28-35, for constant failure rate over time (useful life), are given in Table 4 and Figure 4. Similarly, the estimated changes in State Probabilities of subsystems with time increment of 10 hours, for time dependent failure rate (wear-out phase under assumption that survival function follows Weibull distribution) are given in Table 5 and Figure 5.

It can be observed from Table 4 and Table 5 that under both the circumstances i.e. "useful life" and "wear-out phase", the estimated decrease over time in state probabilities of degraded efficiencies P_3 versus P_5 are very close to each other. Similarly, it is also evident that the estimated decrease over time in state probabilities of P_2 versus P_4 are also observed to be close to each other under both the circumstances. In ANN model, the output (variation in state probabilities at time, $(t + \Delta t)$) are derived by summation of product of weights and input states. The closeness in values of states P_2 versus P_4 and P_3 versus P_5 are due to the two facts (i) this summation is dominated by value of their respective weights rendering cumulative effect of other weights and states as negligible (ii) the values of state probability at time t=0 (input value of states) and are assumed to be similar (0.1 each). Theoretically, this similarity can be explained by the fact that there is only one process working in each of these states and these processes are similar in nature.

As evaluated in Table 4 the estimated increase in failed State probability P_1 was from 5% to 5.5% during 80 hours when failure rates of subsystems are constant over time (useful life period). However, as evaluated in Table 5 it can be observed that estimated value of P_1

increased considerably from 5% to 7% for same time period when failure rates are time-dependent (wear-out phase). The failed state P_1 is reached due to failure of subsystem I which has seven processes. On top of that each process has heavy loaded equipment having tendency to deteriorate rapidly with time thereby affecting the shape parameter (β) of time-dependent failure rate, unless appropriate maintenance strategy is adopted. Both these factors add up to the considerable decrease in state probability P_1 with time when the system goes to deteriorating condition referred to as to wear-out phase in this study.

The changes in respective Upstate and Downstate probabilities, computed using Equation 36 and 37 respectively are given in Table 6 and Figure 6. It is evident that the estimated decrease in upstate probability is from 85% to 84.53% for useful life, and from 85% to 82.87% for wear-out phase. Again, this considerable decrease in downstate probability during wear-out phase is mostly attributed to its direct correlation with P_1.

It can be verified from given data that $P_{upstate} + P_{downstate} = 1$

Table 4

Change in State Probabilities with Time (Subsystems with Constant Failure Rates)

TIME (Hour)	P_0	P_1	P_2	P_3	P_4
0	0.45	0.05	0.1	0.1	0.1
10	0.44944	0.05058	0.09997	0.09992	0.09995
20	0.44889	0.05116	0.09994	0.09984	0.0999
30	0.44833	0.05174	0.09991	0.09975	0.09986
40	0.44778	0.05232	0.09988	0.09967	0.09981
50	0.44722	0.0529	0.09985	0.09959	0.09976
60	0.44667	0.05348	0.09981	0.09951	0.09971
70	0.44612	0.05405	0.09978	0.09943	0.09966
80	0.44557	0.05463	0.09975	0.09935	0.09961

TIME (Hour)	P_5	P_6	P_7
0	0.1	0.05	0.05
10	0.09992	0.05013	0.05009
20	0.09984	0.05027	0.05017
30	0.09975	0.0504	0.05026
40	0.09967	0.05053	0.05034
50	0.09959	0.05066	0.05043
60	0.09951	0.05079	0.05051
70	0.09943	0.05093	0.0506
80	0.09935	0.05106	0.05068

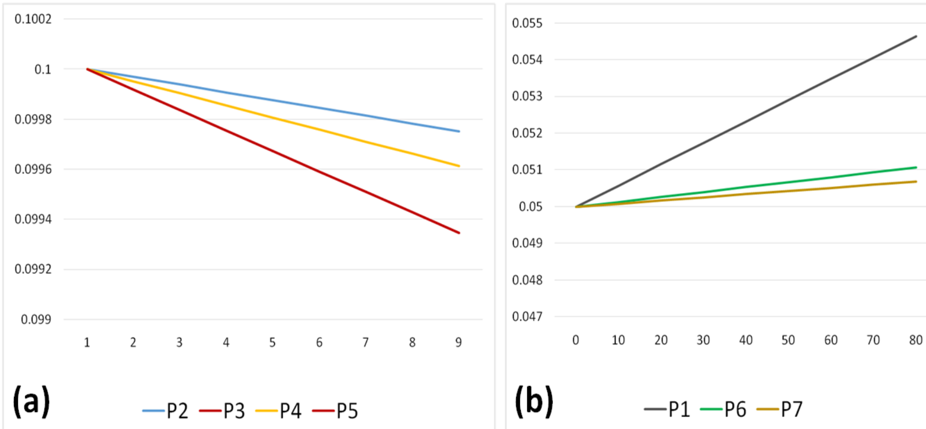


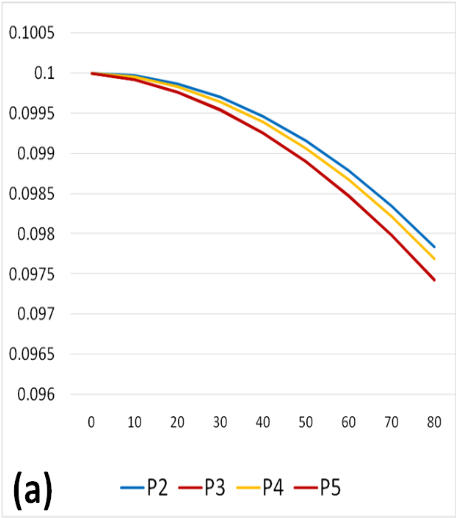
Figure 4. Variation in State Probabilities (a) P_2, P_3, P_4, P_5 (b) P_1, P_6, P_7 with Time (Subsystems with Constant Failure Rates)

Table 5

Change in State Probabilities with Time (Subsystems with Time-Dependent Failure Rates)

TIME (Hour)	P_0	P_1	P_2	P_3	P_4
0	0.45	0.05	0.1	0.1	0.1
10	0.44962	0.05058	0.09997	0.09992	0.09995
20	0.44893	0.05175	0.09987	0.09977	0.09984
30	0.44793	0.05351	0.09971	0.09955	0.09965
40	0.44662	0.05585	0.09947	0.09926	0.09939
50	0.445	0.05878	0.09916	0.0989	0.09907
60	0.44308	0.06228	0.09879	0.09847	0.09868
70	0.44086	0.06634	0.09835	0.09798	0.09822
80	0.43834	0.07097	0.09784	0.09742	0.09769

TIME (Hour)	P_5	P_6	P_7
0	0.1	0.05	0.05
10	0.09992	0.05002	0.050001
20	0.09977	0.05004	0.050003
30	0.09955	0.05007	0.050004
40	0.09926	0.05009	0.050006
50	0.0989	0.05011	0.050007
60	0.09848	0.05013	0.050008
70	0.09799	0.05015	0.05001
80	0.09743	0.05017	0.050011



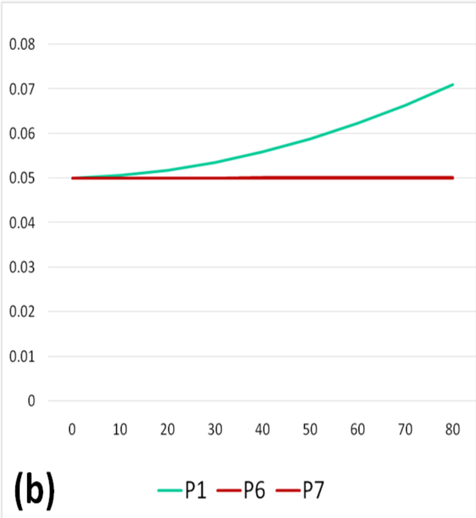


Figure 5. Variation in State Probabilities (a) P_2, P_3, P_4, P_5 (b) P_1, P_6, P_7 with Time (Subsystems with Time Dependent Failure Rates)

Table 6

Variation of Upstate and Downstate Probabilities with Time (Subsystems with Constant Failure Rates v/s Time- Dependent Failure Rates)

	Constant Failure Rate		Time Dependent Failure Rate	
TIME (Hour)	$P_{upstate}$	$P_{downstate}$	$P_{upstate}$	$P_{downstate}$
0	0.85	0.15	0.85	0.15
10	0.8492	0.1508	0.849384	0.1506
20	0.8484	0.1516	0.848177	0.15179
30	0.8476	0.1524	0.846381	0.15358
40	0.84681	0.15319	0.843998	0.15594
50	0.84601	0.15399	0.841035	0.15889
60	0.84522	0.15478	0.837495	0.16242
70	0.84442	0.15558	0.833387	0.16651
80	0.84363	0.15637	0.828719	0.17116

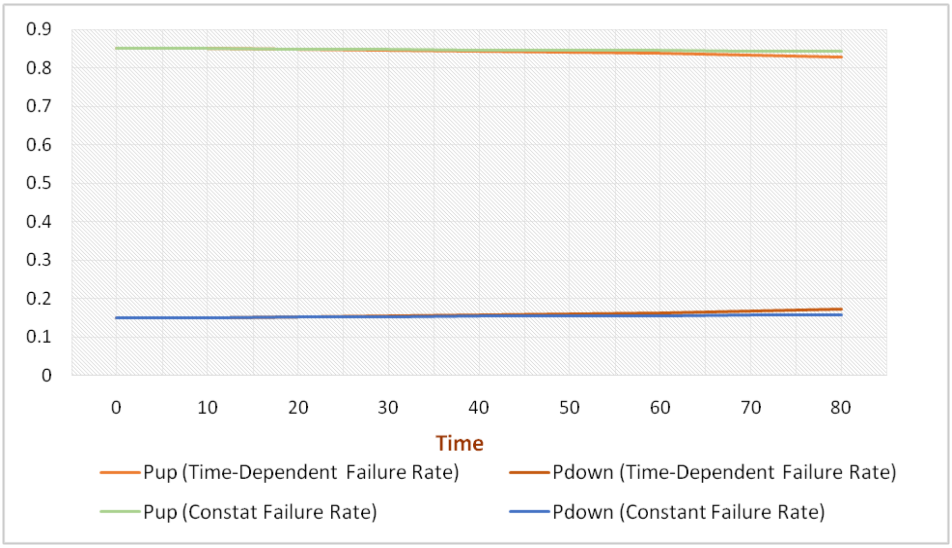


Figure 6. Variation of Upstate and Downstate Probabilities with Time (Subsystems with Constant Failure Rates v/s Time-Dependent Failure Rates)

Profit Analysis Considering Preventive Maintenance (PM)

One of the prominent objectives to estimate reliability of an industrial process is to optimize the costs to maximize the profits. Although, maximizing the uptime probability to more than 90% seems to be an obvious choice. However, its implementation leads to maximizing maintenance costs. There are various maintenance performance measures suited to meet the industrial requirements with objective to minimize costs (Samat et al., 2011), still their implementation affects profit. Many researchers have used reliability parameters to estimate the profit function of various industrial processes (Taneja et al., 2007; Yaqoob et al., 2017; Nasir et al., 2019).

In metal sheet manufacturing plant, total cost consists of many factors including material cost, labour cost, engineering cost including machine running cost, maintenance costs, and overhead cost (Dallan Newsletter, 2017). Profit function, or Expected Total Profit per unit time, is computed by Equation 39 and 40:

$$Profit\ per\ unit\ time\ = K_1 A_0(t) - C_T - C_{PM} \quad [39]$$

K_1= Revenue per unit uptime; $A_0(t)$ =Steady state availability of the system;
C_T = Total Cost per unit time; C_{PM} = Total Cost of PM per unit time

$$C_{PM} = C_{PRS} + C_{DT} \quad [40]$$

Where,

C_{PRS} = *Preventive Replacement and Service Cost;* C_{DT} = *Downtime Cost*

Numerical Computation

Taking K_1 = 14000 US\$, C_T = 8400 US\$ each for time increment Δt = 10 *hour*
Suppose the system enters wear-out phase (deteriorating condition) at $t = 0$, wherein failure rate of each sub-system is time dependent as defined by Equation 38, with shape parameter $\beta = 2.5$ and the respective scale parameters taken in such a manner so as to match the initial failure rates of sub-systems given in Table 3.

To compare profitability of system under different Preventive Maintenance (PM) costs, computed using Equation 40 proposed further actions are enumerated in Table 7.

Table 7

Proposed further actions (i) PM with maximum repairs/replacements (ii) PM with minimum repairs/replacements (iii) Without PM

Proposed Further Actions →	(i) System under PM with maximum repairs/replacement	(ii) System under PM with minimum repairs/replacements	(iii) System without PM
Scheduled PM Cycle	After 2160 hours	After 720 hours	-
Time duration of PM	5 hours	1 hour	0
C_{DT} (@1400\$ per hour)	US \$ 7000	US \$ 1400	0
C_{PRS}	US \$ 3000	US \$ 600	0
C_{PM}	US \$ 10000	US \$ 2000	0
C_{PM} per 10 hours	US \$ 46.29	US \$ 27.77	0

The effects of proposed further actions (Table 7) on system are given below:

(i) System under PM with maximum repairs/replacements

After this PM action, failure rate of each sub-system is defined by Equation 38, but its shape parameter reduces from $\beta = 2.5$ to $\beta = 2$ and initial failure rates are as given in Table 3.

(ii) System under PM with minimum repairs/replacements

After this PM action, failure rate of each sub-system is defined by Equation 38, but its shape parameter reduces from $\beta = 2.5$ to $\beta = 1.5$ and initial failure rates are as given in Table 3.

(iii) No action is taken and condition of the system continues to deteriorate ($C_{PM} = 0$)

Using numerical values of C_{PM} per unit time (10 hours) as given in Table 7 in Equation 39 and using estimated values of State Probabilities modeled by ANN, the variation in profit with respect to time for all three cases mentioned above are given in Table 8 and Figure 7. It is evident that if the system continues to be in working state without undergoing any PM, the profit with respect to time starts declining rapidly after certain period. As discussed earlier, the equipment also used in various processes of metal sheet manufacturing plant are susceptible to quite rapid deterioration and downtime losses are high, therefore PM becomes inevitable. In this particular case, although, the costs per unit time associated with PM strategy of "maximum repairs and replacements" is twice that of PM strategy of "minimum repairs and replacements", but the running costs under it become more profitable over time.

Table 8

Variation in Profit with Time for system under (i) PM with maximum repairs/replacement, (ii) PM with minimum repairs, (iii) Without PM

TIME (Hour)	Profit per unit time (US $)		
	System under PM with max. repairs/replacement	System under PM with min. repairs/replacements	System without PM
0	3453.71	3472.23	3500
10	6931.19	6949.85	6983.12
20	10371.51	10380.29	10399.91
30	13764.65	13738.89	13681.83
40	17102.46	17001.22	16746.67
50	20377.98	20143.17	19501.88
60	23585.04	23141.06	21847.57
70	26718.10	25971.67	23679.27
80	29772.11	28612.35	24890.87

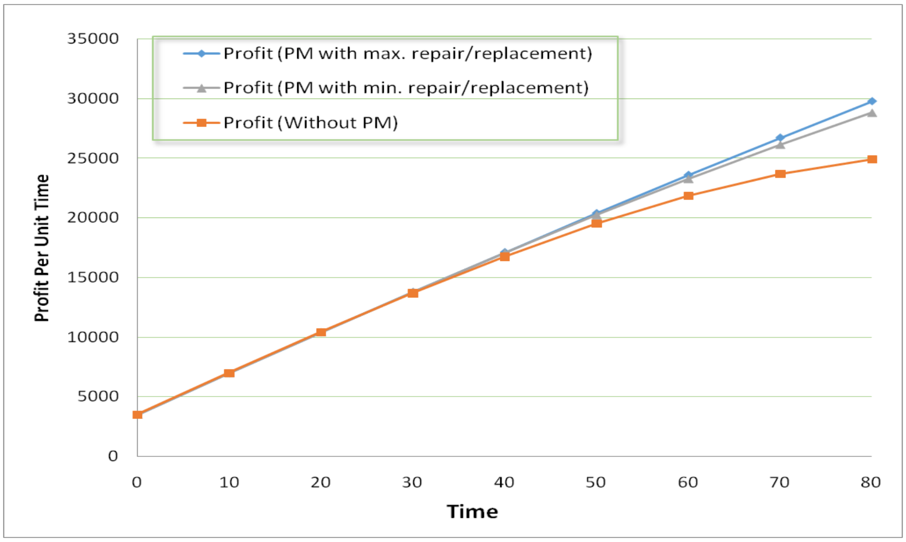


Figure 7. Variation in Profit with Time for system under (i) PM with maximum repair/replacement, (ii) PM with minimum repairs and (iii) Without PM

CONCLUSIONS

In this study, metal sheet manufacturing plant has been considered for examining its reliability in terms of multi-state probabilities of its different efficiency states. The system is susceptible to reach “wear-out phase” rapidly due to its high industrial demand. Therefore, the variations in multi-state probabilities with respect to time have been compared for system’s (i) useful life period and (ii) wear-out phase (deterioration) using ANN model. During “useful life period” of system, failure rates of sub-systems are constant over time. While, during “wear out phase” of system, failure rates of sub-systems tends to increase with time due to deterioration of associated equipment. This factor, in turn, affects the state probabilities over time. These variations in state probabilities were found to decline/increase linearly under system’s “useful life”. While, for “wear-out phase” these variations were mostly found to decline/increase sharply. `

It can also be concluded that the variation in failed state probability, P_1 with time, shows considerable increment during wear-out phase i.e. when failure rates are time-dependent. This effect is cumulatively attributed to more number of processes associated with state P_1 and deterioration of heavy-loaded equipment required in these processes. Similarly, decline in downstate probability was also higher over time when failure rates of sub-systems were assumed to be time-dependent but this influence is mainly due to correlation of downstate probability with P_1.

Considering a particular case of metal sheet manufacturing system the variations in upstate probability were used to estimate and compare the variation in profit per unit time, for system without PM, and under two PM strategies, (i) minimum repairs and replacements, (ii) maximum repairs and replacements. It has been concluded that although, PM strategy with maximum repairs and replacements is costlier, but it is more profitable in the long run.

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