

Estimate Reliability Parameters in Bio_Fuel Plant Using Neural Network Architecture

Ritu Gupta, Ekata, C. M. Batra

Abstract: *The world's ever increasing demand for energy and abating global warming, suitable renewable sources of energy are highly in demand. The wastes from industries such as plant's biomass could meet the energy requirements. In this paper authors analyze bio fuel plant system which produces ethanol fuel. This system is divided into various subsystems considering multiple phases in the production of ethanol. The structure of this system consists of interconnected networks of components on very large dimensional scales escalates the complexity of systems that can increase the degradation of system's functioning. In view of this, one of the computational intelligence approach, neural network (NN), is useful in predicting various reliability parameters. To improve the accuracy and consistency of parameters, Feed Forward Back Propagation Neural Network (FFBPNN) is used. All types of failures and repairs follow exponential distributions. System state probabilities and other parameters are developed for the proposed model using neural network approach. Failures and repairs are treated as neural weights. Neural network's learning mechanism can modify the weights due to which these parameters yield optimal values. Numerical examples are included to demonstrate the results. The iterations are repeated till the convergence in the error tends up to 0.0001 precision using MATLAB code. The reliability and cost analysis of the system can help operational managers in taking the decision to implement it in the real time systems.*

Index Terms: *Neural Network, Back Propagation, Neural Weights, Profit Function, Reliability, Stochastic Process*

I. INTRODUCTION

In recent era, development in the field of science and technology increases the complexity of industrial system for the ease of human comfort, *but at the cost of our environment*. First industry was invented by United Kingdom for massive increase in agriculture in 18th century for the benefit of human. During World War II (1939), United States traced that probability principle that was utilized in power generation problems. On the other side, Germany initialized the optimization and reliability in armaments. All these techniques/ inventions and its optimization with reliability principals play a crucial role in rapid increase in technology. As technology increases,

Revised Manuscript Received on September 03, 2019

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complexity of the system also escalate that degrades the functioning of system and intensifies failure conditions. Some other reasons for failures are the defect in designs, material deficiency, unavoidable complexities, lack of maintenance etc. Reliability analysis helps in identification of the technical circumstances that can affect the system and help in predicting the system life in the future. To solve reliability problems, one needs to identify assumptions/ constraints of dependences or interdependences of units/ component of the system [1]-[2]. To increase the reliability of the system using standby unit with or without waiting time to repair using the supplementary variable technique have been investigated [3]-[5]. A lot of studies dealing with the reliability and profit of systems have been conducted and analyzed the system behavior, reliability and profit function with respect to time. The various reliability parameters of a multi-component system under common cause failure have been studied by many researchers [5]-[6]. As well as many techniques/ methodology are used to evaluate the reliability, some of these are supplementary variable technique, Petri nets, stochastic reward nets, regenerative point technique etc. [7]-[15]. All these conventional methods evaluate the reliability parameters accurately but today's demand is to update the output and minimize the errors/ failures and optimize the results.

According to demand of present era, soft computing techniques (like neural network approach, fuzzy logic, probabilistic reasoning, Genetic algorithm, etc.) have been utilized to determine and optimize complex engineering/ mathematical problems [8]-[11]. Neural network designs are computing techniques which inspired by the models of the biological neuron system of human brain to recognize the relation between input and output. These networks comprise three components:

- Large set of structural neurons
- Well connected network architecture
- Learning algorithm, to train the system.

Proposed neural network consists of a three layers structure which consists of:

- *Input layer*, communicates with environment and takes input
- *Hidden layer*, intermediate layer to update the weights and input/ output between input and output layers
- *Output layer*, presents the results to the user.

These layers are interconnected with synaptic links that carrying the weights and the networks can naturally learn through complex relationships between data

and learning mechanisms. Learning algorithms describe the process to adjust/update weights using activation function and minimize the errors of the weights by applying gradient descent method in back propagation algorithm [12]. The back propagation algorithm was originally introduced in the 1970s and used to train the system network and minimize the error up to required precision.

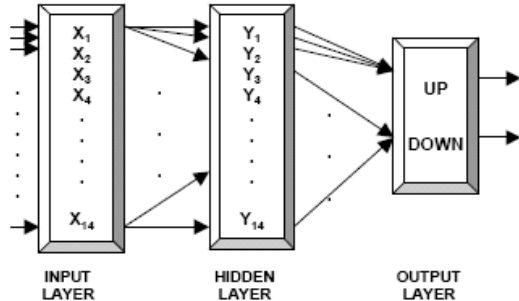


Fig. 1: Neural Network Structure

II. SYSTEM DESCRIPTION

In current scenario, energy demand is increasing rapidly. The shortage of fossil fuels and inadequate resources for oil based energy production have led to research focusing on the optimum use of non-conventional renewable energy resources. In particular, fuel produced from renewable resources such as plant biomass, vegetable oils and industrial wastes are considered carbon neutral because the carbon dioxide released by their combustion is balanced by carbon dioxide absorbed by the plants. The use of bio_fuels as an accompaniment to petroleum-based fuels can also lead to cleaner combustion with fewer carbon monoxide and particulate emissions [13]-[14].

Ethanol is one of the promising and appropriate sources of renewable energy to meet the growing global demand for energy and the fight against global warming by limiting the addition of carbon dioxide from the Earth to the atmosphere. Fermented sugar in biomass materials such as in rice straw, corn, and agricultural residues produce bio-ethanol, that is utilized in engines for internal combustion either in pure form or as a petrol additive.

The bio fuel plant consists of twelve subsystems viz.:

1. Subsystem 1(S1) - *Cleaning Unit of Biomass*: This unit washed out impurities like soil, sand etc.
2. Subsystem 2(S2)- *Chunking Unit*: It is used to cut sugar beet into slices and forwarded to diffuser
3. Subsystem 3(S3)- *Diffusing Unit*: In this unit raw juice is extracted from slices of sugar beets.
4. Subsystem 4 & 5 (S4 & S5) - *2 Filters*: The raw juice from diffuser is filtered in this unit by nano filtration process. Subsystem S5 act as standby unit for filtration process so that the working of system is not halted if S4 unit fails.
5. Subsystem 6(S6)- *Retenate Fermentation unit*: From the filtration unit, Retentate sent for fermentation in this unit.

6. Subsystem 7(S7)- *Crystallization unit*: In this unit crystallization of permeate is carried out.
7. Subsystem 8 (S8)- *Mother Liquor Fermentation unit* : In this unit mother liquor is fermented.
8. Subsystem 9(S9)- *Molasses fermentation unit*: In this unit molasses are fermented.
9. Subsystem 10(S10)- *Distillation unit* - Bio Ethanol produced after fermentation process contains water and other volatile substances which are distilled in this unit.
10. Subsystem 11(S11)- *Refining unit*: Bio ethanol is refined in this unit.
11. Subsystem 12(S12)- *Storage unit*: This is the storage unit of bio ethanol where it is ready to supply as green fuel.

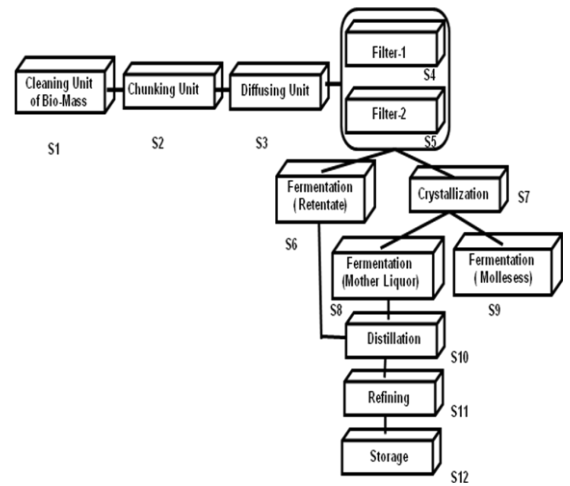


Fig. 2: Block Diagram

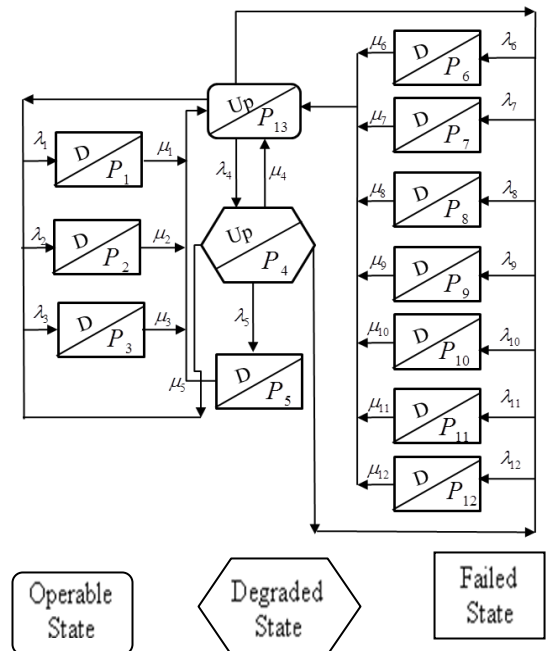


Fig. 3: Transition State Diagram

Keeping these facts in mind, authors established the mathematical model for bio_fuel plant and evaluate various parameters using neural network approach. All hardware failures and repairs time

treated as weights in neural network approach. Rajasekaran et. al. [9] explained the back propagation algorithm in neural network approach to improve the results. Neural networks' learning mechanism (Back Propagation) is used to modify the weights in number of iterations due to which these parameters yield improved results. The MATLAB programming has been developed to demonstrate the results using Back propagation. The main objective of this paper is to target the new coding method to predict the reliability and cost of bio_fuel plant using FFBP algorithm of neural network.

III. ASSUMPTIONS

1. At first, all units are fully functional.
2. The system consists of 12 subsystems
3. The system may fail completely due to failure of S1,S2,S3, S5,S6,S7,S8,S9,S10,S11 and S12.
4. The system is functional due to failure of subsystem S4
5. All system failures and repairs are statistically independent.
6. Failures and repairs of the system are established as neural weights.
7. The residual subsystem can not fail from the failed state.
8. The repaired subsystem(s) function as new.

IV. NOTATIONS

$P_i(t)$	Probability of i^{th} state at any time t , $i = 1, 2, \dots, 13$
$P_i(t+\Delta t)$	Probability of i^{th} state at time $(t+\Delta t)$, $i = 1, 2, 3, \dots, 13$
λ_i	Hardware failure, due to failure of i th unit, $i = 1, 2, \dots, 12$
μ_i	Hardware repair of i th unit, $i = 1, 2, \dots, 12$

V. SOLUTION OF THE MODEL

To investigate the reliability and profit function of the system, neural network approach is considered

$$P_1(t + \Delta t) = (1 - \mu_1 \Delta t)P_1(t) + \lambda_1 \Delta t P_{13}(t) + \lambda_1 \Delta t P_4(t) \quad (1)$$

$$P_2(t + \Delta t) = (1 - \mu_2 \Delta t)P_2(t) + \lambda_2 \Delta t P_{13}(t) + \lambda_2 \Delta t P_4(t) \quad (2)$$

$$P_3(t + \Delta t) = (1 - \mu_3 \Delta t)P_3(t) + \lambda_3 \Delta t P_{13}(t) + \lambda_3 \Delta t P_4(t) \quad (3)$$

$$P_4(t + \Delta t) = \left(1 - \left(\lambda_1 + \lambda_2 + \lambda_3 + \lambda_5 + \lambda_6 + \lambda_7 + \lambda_8 \right) \Delta t \right) P_4(t) + \lambda_4 \Delta t P_{13}(t) \quad (4)$$

$$P_5(t + \Delta t) = (1 - \mu_5 \Delta t)P_5(t) + \lambda_5 \Delta t P_4(t) \quad (5)$$

$$P_6(t + \Delta t) = (1 - \mu_6 \Delta t)P_6(t) + \lambda_6 \Delta t P_{13}(t) + \lambda_6 \Delta t P_4(t) \quad (6)$$

$$P_7(t + \Delta t) = (1 - \mu_7 \Delta t)P_7(t) + \lambda_7 \Delta t P_{13}(t) + \lambda_7 \Delta t P_4(t) \quad (7)$$

$$P_8(t + \Delta t) = (1 - \mu_8 \Delta t)P_8(t) + \lambda_8 \Delta t P_{13}(t) + \lambda_8 \Delta t P_4(t) \quad (8)$$

$$P_9(t + \Delta t) = (1 - \mu_9 \Delta t)P_9(t) + \lambda_9 \Delta t P_{13}(t) + \lambda_9 \Delta t P_4(t) \quad (9)$$

$$P_{10}(t + \Delta t) = (1 - \mu_{10} \Delta t)P_{10}(t) + \lambda_{10} \Delta t P_{13}(t) + \lambda_{10} \Delta t P_4(t) \quad (10)$$

$$P_{11}(t + \Delta t) = (1 - \mu_{11} \Delta t)P_{11}(t) + \lambda_{11} \Delta t P_{13}(t) + \lambda_{11} \Delta t P_4(t) \quad (11)$$

$$P_{12}(t + \Delta t) = (1 - \mu_{12} \Delta t)P_{12}(t) + \lambda_{12} \Delta t P_{13}(t) + \lambda_{12} \Delta t P_4(t) \quad (12)$$

$$P_{13}(t + \Delta t) = \left(1 - \left(\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_6 + \lambda_7 \right) \Delta t \right) P_{13}(t) + \mu_1 \Delta t P_1(t) + \mu_2 \Delta t P_2(t) + \mu_3 \Delta t P_3(t) + \mu_4 \Delta t P_4(t) + \mu_5 \Delta t P_5(t) + \mu_6 \Delta t P_6(t) + \mu_7 \Delta t P_7(t) + \mu_8 \Delta t P_8(t) + \mu_9 \Delta t P_9(t) + \mu_{10} \Delta t P_{10}(t) + \mu_{11} \Delta t P_{11}(t) + \mu_{12} \Delta t P_{12}(t) \quad (13)$$

Neural weights are

$$w_{(13)1} = \lambda_1 \Delta t, \quad w_{(13)2} = \lambda_2 \Delta t, \quad w_{(13)3} = \lambda_3 \Delta t,$$

$$w_{(13)4} = \lambda_4 \Delta t, \quad w_{(13)5} = 0, \quad w_{(13)6} = \lambda_6 \Delta t,$$

$$w_{(13)7} = \lambda_7 \Delta t, \quad w_{(13)8} = \lambda_8 \Delta t, \quad w_{(13)9} = \lambda_9 \Delta t,$$

$$w_{(13)(10)} = \lambda_{10} \Delta t, \quad w_{(13)(11)} = \lambda_{11} \Delta t,$$

$$w_{(13)(12)} = \lambda_{12} \Delta t$$

$$w_{(13)(13)} = 1 - \left(\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_6 + \lambda_7 \right) \Delta t + \left(\lambda_8 + \lambda_9 + \lambda_{10} + \lambda_{11} + \lambda_{12} \right) \Delta t$$

$$w_{1(13)} = \mu_1 \Delta t, \quad w_{11} = 1 - \mu_1 \Delta t,$$

$$w_{12} = w_{13} = w_{14} = w_{15} = w_{16} = w_{17} = 0$$

$$w_{18} = w_{19} = w_{1(10)} = w_{1(11)} = w_{1(12)} = 0$$

$$w_{2(13)} = \mu_2 \Delta t, \quad w_{21} = 0, \quad w_{22} = 1 - \mu_2 \Delta t,$$

$$w_{23} = w_{24} = w_{25} = w_{26} = w_{27} = w_{28} = 0$$

$$w_{29} = w_{2(10)} = w_{2(11)} = w_{2(12)} = 0$$

$$w_{3(13)} = \mu_3 \Delta t, \quad w_{31} = w_{32} = 0,$$

$$w_{33} = 1 - \mu_3 \Delta t,$$

$$w_{34} = w_{35} = w_{36} = w_{37} = w_{38} = 0$$

$$w_{39} = w_{3(10)} = w_{3(11)} = w_{3(12)} = 0$$

$$w_{4(13)} = \mu_4 \Delta t, \quad w_{41} = \lambda_1 \Delta t, \quad w_{42} = \lambda_2 \Delta t$$

$$w_{43} = \lambda_3 \Delta t, \quad w_{45} = \lambda_5 \Delta t, \quad w_{46} = \lambda_6 \Delta t,$$

$$w_{44} = \left(1 - \left(\lambda_1 + \lambda_2 + \lambda_3 + \lambda_5 + \lambda_6 + \lambda_7 + \lambda_8 + \lambda_9 + \lambda_{10} + \lambda_{11} + \lambda_{12} + \mu_4 \right) \Delta t \right)$$

$$w_{47} = \lambda_7 \Delta t, w_{48} = \lambda_8 \Delta t, w_{49} = \lambda_9 \Delta t$$

$$w_{4(10)} = \lambda_{10} \Delta t, w_{4(11)} = \lambda_{11} \Delta t, w_{4(12)} = \lambda_{12} \Delta t$$

$$w_{5(13)} = \mu_5 \Delta t, w_{55} = 1 - \mu_5 \Delta t,$$

$$w_{51} = w_{52} = w_{53} = w_{54} = w_{56} = w_{57} = 0$$

$$w_{58} = w_{59} = w_{5(10)} = w_{5(11)} = w_{5(12)} = 0$$

$$w_{6(13)} = \mu_6 \Delta t, w_{66} = 1 - \mu_6 \Delta t,$$

$$w_{61} = w_{62} = w_{63} = w_{64} = w_{65} = w_{67} = 0$$

$$w_{68} = w_{69} = w_{6(10)} = w_{6(11)} = w_{6(12)} = 0$$

$$w_{7(13)} = \mu_7 \Delta t, w_{77} = 1 - \mu_7 \Delta t,$$

$$w_{71} = w_{72} = w_{73} = w_{74} = w_{75} = w_{76} = 0$$

$$w_{78} = w_{79} = w_{7(10)} = w_{7(11)} = w_{7(12)} = 0$$

$$w_{8(13)} = \mu_8 \Delta t, w_{88} = 1 - \mu_8 \Delta t,$$

$$w_{81} = w_{82} = w_{83} = w_{84} = w_{85} = w_{86} = 0$$

$$w_{87} = w_{89} = w_{8(10)} = w_{8(11)} = w_{8(12)} = 0$$

$$w_{9(13)} = \mu_9 \Delta t, w_{99} = 1 - \mu_9 \Delta t,$$

$$w_{91} = w_{92} = w_{93} = w_{94} = w_{95} = w_{96} = 0$$

$$w_{97} = w_{98} = w_{9(10)} = w_{9(11)} = w_{9(12)} = 0$$

$$w_{(10)(13)} = \mu_{10} \Delta t, w_{(10)(10)} = 1 - \mu_{10} \Delta t,$$

$$w_{(10)1} = w_{(10)2} = w_{(10)3} = w_{(10)4} = w_{(10)5} = w_{(10)6} = 0$$

$$w_{(10)7} = w_{(10)8} = w_{(10)9} = w_{(10)(11)} = w_{(10)(12)} = 0$$

$$w_{(11)(13)} = \mu_{11} \Delta t, w_{(11)(11)} = 1 - \mu_{11} \Delta t,$$

$$w_{(11)1} = w_{(11)2} = w_{(11)3} = w_{(11)4} = w_{(11)5} = w_{(11)6} = 0$$

$$w_{(11)7} = w_{(11)8} = w_{(11)9} = w_{(11)(10)} = w_{(11)(12)} = 0$$

$$w_{(12)(13)} = \mu_{12} \Delta t, w_{(12)(12)} = 1 - \mu_{12} \Delta t,$$

$$w_{(12)1} = w_{(12)2} = w_{(12)3} = w_{(12)4} = w_{(12)5} = w_{(12)6} = 0$$

$$w_{(12)7} = w_{(12)8} = w_{(12)9} = w_{(12)(10)} = w_{(12)(11)} = 0$$

VI. FEEDFORWARD BACK PROPAGATION NEURAL NETWORK ALGORITHM OF THE SYSTEM

Step 1: Consider number of inputs and outputs

Step 2: Suppose the number of neurons in hidden layer.

Step 3: Initialize the weight matrices

[W]: Weights of synapses connecting input and hidden layer.

[V]: Weights of synapses connecting hidden and output layer.

Step 4: Calculate inputs of hidden layer

$$I_h = W^T * O_i$$

[W^T]: Transpose of weight matrix connecting input and hidden layer.

[O_i]: Output of Input Layer

Step 5: Calculate output of hidden layer using sigmoidal

$$\text{function, } O_h = \left\{ \frac{1}{1 + e^{-I_{hi}}} \right\}$$

Step 6: Calculate inputs of output layer

$$I_o = V^T * O_h$$

[V^T]: Transpose of weight matrix connecting hidden and output layer.

[O_h]: Output of hidden Layer

Step 7: Calculate output of output layer using sigmoidal

$$\text{function, } O_o = \left\{ \frac{1}{1 + e^{-I_{oi}}} \right\}$$

Step 8: Evaluate the error

Step 9: If error < tolerance

then End the learning process.

Else

Update weight matrices [V] and [W]

increment the epochs by 1

go to Step 4

else End the learning process

Neural network structure (Figure 1) demonstrates the inputs of neural network that can be represented by X_i and expressed by following equations:

$$X_i = P_i(t); \text{ where } i = 1, 2, \dots, 13 \quad \dots(14)$$

As well as the outputs of neurons of considered system is expressed by Y_i . With the help of transition states (Figure 3) one can have following output equations:

$$Y_i = P_i(t + \Delta t), \text{ where } i = 1, 2, \dots, 13 \quad (15)$$

$$Y_{13} = w_{00} X_{13} + w_{1(13)} X_1 + w_{2(13)} X_2 + w_{3(13)} X_3 + w_{4(13)} X_4 + w_{5(13)} X_5 + w_{6(13)} X_6 + w_{7(13)} X_7 + w_{8(13)} X_8 + w_{9(13)} X_9 + w_{(10)(13)} X_{10} + w_{(11)(13)} X_{11} + w_{(12)(13)} X_{12} \quad (16)$$

$$Y_1 = w_{11} X_1 + w_{(13)1} X_{(13)} + w_{41} X_4 \quad (17)$$

$$Y_2 = w_{22} X_2 + w_{(13)2} X_{(13)} + w_{42} X_4 \quad (18)$$

$$Y_3 = w_{33} X_3 + w_{(13)3} X_{(13)} + w_{43} X_4 \quad (19)$$

$$Y_4 = w_{44} X_4 + w_{(13)4} X_{(13)} \quad (20)$$

$$Y_5 = w_{55} X_5 + w_{45} X_4 \quad (21)$$

$$Y_6 = w_{66} X_6 + w_{(13)6} X_{(13)} + w_{46} X_4 \quad (22)$$

$$Y_7 = w_{77} X_7 + w_{(13)7} X_{(13)} + w_{47} X_4 \quad (23)$$

$$Y_8 = w_{88}X_8 + w_{(13)8}X_{(13)} + w_{48}X_4 \quad (24)$$

$$Y_9 = w_{99}X_9 + w_{(13)9}X_{(13)} + w_{49}X_4 \quad (25)$$

$$Y_{10} = w_{(10)(10)}X_{(10)} + w_{(13)(10)}X_{(13)} + w_{4(10)}X_4 \quad (26)$$

$$Y_{11} = w_{(11)(11)}X_{(11)} + w_{(13)(11)}X_{(13)} + w_{4(11)}X_4 \quad (27)$$

$$Y_{12} = w_{(12)(12)}X_{(12)} + w_{(13)(12)}X_{(13)} + w_{4(12)}X_4 \quad (28)$$

Combining the outputs of up and down states distinctly from the basic probabilistic equations (16)-(28), one may obtain the up and down state probabilities. The reliability and profit function of the considered system can be expressed as:

$$P_{up}(t) = Y_{13} + Y_4 \quad \dots(29)$$

$$P_{down}(t) = 1 - P_{up} \quad \dots(30)$$

$$\text{Reliability} = Y_{13} + Y_4 \quad \dots(31)$$

$$G(t) = C_1 \times P_{up} - C_2 \times t \quad \dots(32)$$

where C_1 : revenue cost

C_2 : repair cost per unit time

$P_{up}(t)$: Probability of operable states

VII. NUMERICAL EXAMPLE

To analyze the results, authors assume the following data for repairable system

$$a = 0.8; \mu_i = 1; \lambda_i = 0.01$$

- Equation (31) yields the reliability of the system by FFBP neural network approach. Table I and Figure 4 show the desired reliability nearer to 1 up to error tolerance 10^{-4} and its graphical representation respectively.

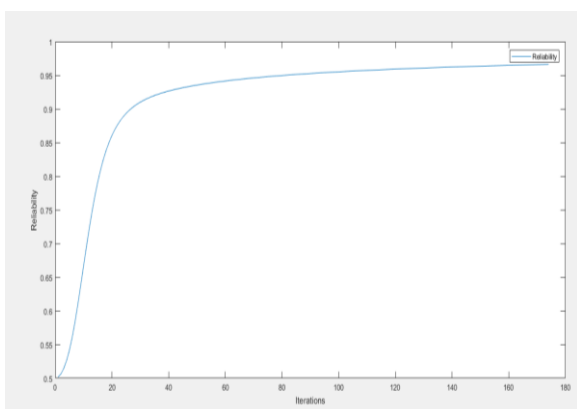


Fig. 4: Optimise Reliability with Iteration

Table I. Reliability with iteration

Iterations	Reliability
1	0.5018

15	0.7913
30	0.9100
45	0.9314
60	0.9414
75	0.9479
90	0.9526
105	0.9562
120	0.9591
135	0.9615
150	0.9635
165	0.9652
174	0.9661

- Applying values on equation (32), one can obtain the different values of the profit function of the system. Consider the revenue cost $C_1=1$ and various values of repair cost, $C_2 = 0.2, 0.4, 0.5$. Values of the profit function obtained is listed in Table II and depicted graphically in Figure 7.

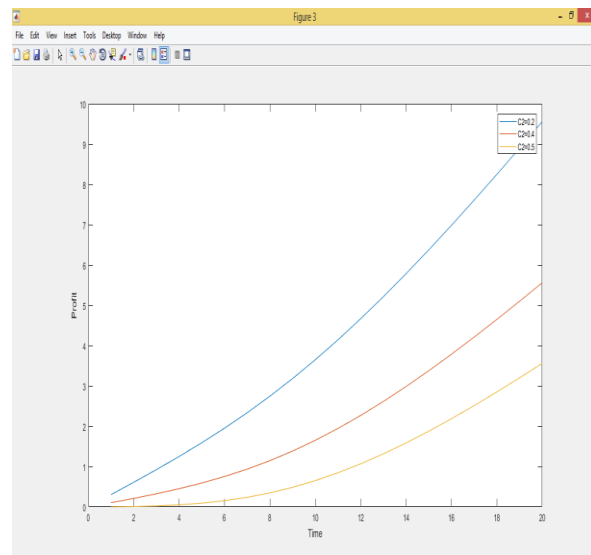


Fig 5 :Time vs Comparative profit

Table II. Time Vs Comparative Cost

TIME	PROFIT		
	C2=0.2	C2=0.4	C2=0.5
1	0.301823	0.101823	0.001823
2	0.608094	0.208094	0.008094
3	0.922506	0.322506	0.022506
4	1.248542	0.448542	0.048542
5	1.589966	0.589966	0.089966
6	1.950759	0.750759	0.150759
7	2.334623	0.934623	0.234623
8	2.744497	1.144497	0.344497
9	3.182293	1.382293	0.482293
10	3.648805	1.648805	0.648805
11	4.143757	1.943757	0.843757

12	4.665968	2.265968	1.065968
13	5.213569	2.613569	1.313569
14	5.784263	2.984263	1.584263
15	6.375558	3.375558	1.875558
16	6.98496	3.78496	2.18496
17	7.610107	4.210107	2.510107
18	8.248845	4.648845	2.848845
19	8.899269	5.099269	3.199269
20	9.559723	5.559723	3.559723

VIII. CONCLUSION

The neural networks approach can be an effective and efficient way for computing and thus improving the reliability and cost function of the system by learning and modifying mechanism of weights. It has vast area of applications including many approaches. One of them is feed forward back propagation neural network approach that provides reliability 0.5018 initially as shown in Figure 4 and Table I. After increment in iterations, the weights (failures/repairs) are modified using gradient descent method of back propagation of neural network and improve the reliability with tolerance 10^{-4} . Table I depicts that in 174 iterations, 0.9661 reliability is attained. The improvement in reliability obtained after application of FFBPNN suggests how important this technique can be, especially keeping in mind the existence of the complex modern engineering system. Equation (32) yields the cost as shown in Figure 5 and Table II. On examination of the results, that it is consistently increasing with respect to epochs.

The near to precision determination of system reliability is a key factor in maximizing the system availability. So authors achieved the reliability of the considered system upto 96.61% with tolerance 10^{-4} . It is hoped that this work will serve as a valuable resource for industries and optimization reliability in real time applications.

REFERENCES

1. D.R. Cox, "Analysis of non-Markovian Stochastic processes by the inclusion of Supplementary variables" Proc.Comb.Phil. Soc. 51, 1955, pp 433-441.
2. Igor Bazovsky, Reliability Theory and Practice, PHI Englewood cliff, NJ., 1961.
3. J. Singh and P. Goyal, "Availability analysis of a standby complex system having imperfect switch over device" Microelectron Reliab. 35, 1996, 285-288
4. M. Ram, S.B. Singh and V.V. Singh, "Stochastic analysis of a standby system with waiting repair strategy", IEEE transactions on systems, man, and cybernetics: systems, 43(3), 2013.
5. G. Levitin, L. Xing and Y. Dai, "Reliability versus expected mission cost and uncompleted work in heterogeneous warm standby multiphase systems", IEEE Transactions on Systems, Man, and Cybernetics: Systems, 47(3), 2017, pp 462 – 473.
6. V.V. Singh., S.B. Singh, M. Ram and C.K. Goel, "Availability Analysis of a system having three units: Super priority, Priority and Ordinary under pre-emptive resume repair policy", International Journal of reliability and Applications, 11(1), 2010, pp. 41-53.
7. Anish Sachdeva, Dinesh Kumar and Pradeep Kumar, "Reliability analysis of pulping system using Petri nets", International Journal of Quality & Reliability Management 25(8), 2008, pp.860-877. DOI: 10.1108/02656710810898667

8. S. Rajasekaran and G.A. Vijaylakshmi Pai, Neural Networks, Fuzzy Logic, and Genetic Algorithm, PHI, 2004.
9. N. Karunanithi, D. Whitley and Y.K. Malaiya, "Using neural networks in reliability", IEEE, 9, 1992, pp. 53-59.
10. Ekata, N. Gupta and S.B. Singh, "Operational availability of marine vehicle system using neural network approach", International Journal of Computational Science and Mathematics (IJCSM), 2, 2010, pp. 91-99
11. Ekata, N. Sharma and C.M. Batra, "Neural network approach for analytical study of the reliability of refrigeration system" IEEE International Conference on Innovative Applications of Computational Intelligence on Power, Energy and Controls with their impact on Humanity (CIPECH-14) at KIET, Ghaziabad, India, 2014, pp. 511-514
12. I. Lakshman and S. Ramaswamy "An Artificial Neural-Network Approach to Software Reliability Growth Modeling", Procedia Computer Science. 57, 2015, pp. 695-702.
13. Qian Kang, Lise Appels, Tianwei Tan, and Raf Dewil, "Bioethanol from Lignocellulosic Biomass: Current Findings Determine Research Priorities, Review Article, The Scientific World Journal, Hinwai Publishing Cooperation, 2014, Article ID 298153, 13 pages, http://dx.doi.org/10.1155/2014/298153
14. Ahmet Ozan Gezerman, Mehmet Cercis Erişmiş, "Anhydrous Ethanol Production from Sugar-Beet Pulp", International Journal of Modern Chemistry, 2012, 2(2) pp. 41-46
15. Xiang-Yu Li, Hong-Zhong Huang, Yan-Feng Li, "Reliability analysis of phased mission system with non-exponential and partially repairable components", Reliability Engineering and System Safety 175, 2018, pp. 119-127.

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