Comparison between Multi-Layer Perceptron and Radial Basis Function Networks for Predicting Reliability and Availability: A Case Study

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Abstract: The rapidly growing field of Artificial Neural Network (ANN) applications has witnessed several admirable contributions. This paper presents application of ANN for predicting the improved values of reliability and availability after successful implementation of reliability centered maintenance (RCM) policy in a thermal power plant. In this study, the predictive performance of two Artificial Neural Networks, viz-a-viz Radial Basis Function (RBF) and Multi-Layer Perceptron (MLP) were compared. The reliability and availability of any component and/or sub-system can be calculated mathematically (using traditional approach) by knowing the two parameters i.e. outage hours and number of faults. However in the said problem, after implementation of new maintenance policy, outage hours decrease and this is the only known parameter. The second parameter (number of faults) is unknown. The importance of MLP based and RBF based ANN model is to predict reliability and availability on the basis of only one parameter known. The test results showed that outcome of proposed ANN model is in good agreement with desired or actual results. The MLP network produced a more fitted output to the cross validation data set than the RBF network. This application of ANN helped knowing foreseen indices and convincing maintenance department about benefits of implementation of RCM.

Keywords: ANN, MLP, RBF, Availability, Reliability, Thermal power plant, Outages and RCM.

Introduction

ANN is an information processing paradigm which is inspired from the method of processing information by the biological nervous systems (brain). Thus it is a system modeled, based on the human brain. ANN models can learn by examples just like humans [1,2]. In this paper, an attempt has been made to simulate problem using MLP and RBF networks of ANN having multiple layers of neurons. Each neuron is associated to a few of its neighbors with varying coefficients of connectivity. These coefficients signify the strengths of the connections. Learning is accomplished by adjusting these strengths to cause the overall network to produce appropriate results. Neural networks can find dependencies between several variables [3,4]. That means these networks can recognize situations which are of the same kind as the situations during the learning of the neural network. Neural network consists of simple processing units called neurons and having three layers namely the input, output and the hidden layers. The neurons in the input layer receive input from the external space. This layer does not perform any computations. The hidden layer receives inputs from the input layer and performs computation and provides the outputs to the output layer. Output layer consists of neurons that communicate the output of the system to the user or external environment [5]. As the human brain learns from experience, similarly changing of connection weights of ANN causes the network to learn the solution to a problem. The strength of the connection between the neurons is stored as a weight value for the particular connection. ANN is supposed to be trained if it is capable of providing the exact solutions when test data, which is different from training data, is presented to it. The most commonly used networks of ANN are multilayer perceptron (MLP) and Radial Basis Function (RBF).

MLP network gets trained using back propagation algorithm. It consists of multiple layers of computational units, neurons, that are connected in a feed-forward way. The basic structure of MLP consists of an input layer, one or more hidden layers and one output layer as shown in Fig. 1. The output from a unit is used as input to units in the subsequent layer. The connection between units in subsequent layers has an associated weight which is computed using error back propagation algorithm.

RBF is another popular architecture used in ANN, which is multilayer and feed-forward, is often used for strict interpolation in multi-dimensional space. The neurons are organized as layers in a layered neural network [6]. The basic architecture of a three-layered neural network is shown in Fig. 1.

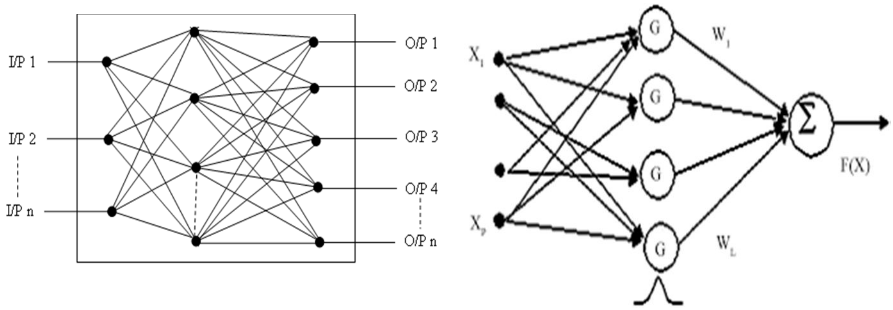


Fig. 1.Basic Structure of MLP and RBF Neural Network

RCM based proposed plans have resulted in improving the uptime (hence reducing outage time) of the components in the plant. The parameters availability, A(t) and reliability, R(t) are functions of two variables i.e. outage time and number of failures. RCM plan improves the reliability and availability of individual component and thus outage time decreases. With this one (outage time) known variable as input, the accurate parameter [A(t) & R(t)] estimation can be done by using software models for the testing phase [7]. Keeping this in view, an approach of using ANN models for parameter predictions has been studied. Design of ANN model for estimation of improved values of A(t) and R(t) of the components has been presented in this paper.

ANN model for Prediction

The water wall tube (WWT) is one component at thermal power plant which is responsible for most of the outage time. Hence WWT has been identified as most critical and RCM methodology has been proposed for it. The implementation of RCM has shown decline in outage hours of WWT. This decline of outages enhances A(t) and R(t) of the plant. Similarly RCM enhances A(t) and R(t) of the other components for which it has been proposed. An ANN model has been presented here for prediction of enhanced A(t) and R(t) of rest of the components to be considered for RCM later. This will help convincing maintenance department for the implementation of RCM. Importance of this model is to predict A(t) and R(t) on the basis of only one parameter i.e. outage hours however traditional approach requires one additional parameter i.e. number of faults which is unavailable for the said problem.

In the proposed ANN model, outage hours have been taken as input and it gives the value of R(t) and A(t) as output. The MLP and RBF networks with Logistic activation function and Hyperbolic Tangent activation function in first and second hidden layer are used respectively. The back propagation algorithm from Neural Network Toolbox™ of MATLAB software, is used as training function [8]. Trainlm is a network training function that updates weight and bias values according to Levenberg – Marquardt algorithm [9]. The data set is prepared from outage review report of WWT collected from the plant and calculated values of R(t) and A(t). The data set consists of outage hours and corresponding values of R(t) and A(t) and is used to train proposed ANN model. The trained ANN model is tested against the selected values of R(t) and A(t) which are not included in data set and results of ANN model have been compared with actual/desired values available.

Table 1 gives the comparison of desired output and ANN output (MLP network) for R(t) of WWT and also shows the absolute value of error between the two.

Table 1 ANN Model (MLP) Test Results for R(t) of WWT

Sr. No.	Outage Hours (ANN Input)	Reliability R(t)		Error (Absolute value)
		Desired Output	ANN Output (MLP)	
1.	24.20	0.9972	0.9952	0.0020
2.	305.50	0.6830	0.6704	0.0126
3.	214.10	0.8622	0.8297	0.0325
4.	1636.50	0.0061	0.0067	0.0006
5.	100.00	0.9580	0.9765	0.0185

As the error is negligible (almost zero), hence it is proved that the results of proposed ANN model (MLP) are in good agreement with desired/actual results. The ANN results are also compared graphically with the actual results and are shown in Fig. 2 justifying the good agreement between the two. Fig. 3 shows the magnitude of error between desired and simulated (ANN) values of reliability.

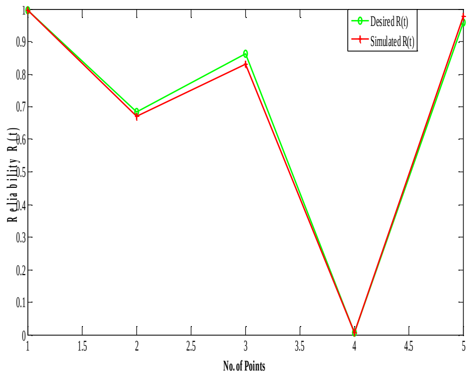


Fig. 2. Comparison of Desired and ANN (MLP) Results of R(t)

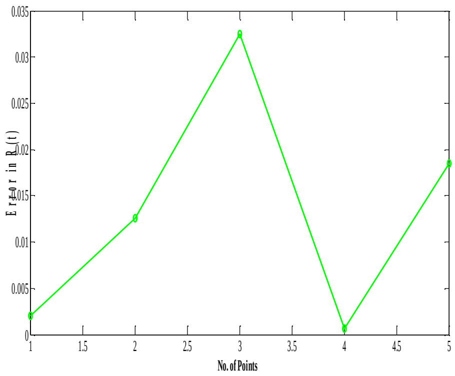


Fig. 3. Error in Values of R(t)

Table 2 show the absolute value of error between desired output and ANN output (MLP network) for different values of A(t) for WWT.

Table 2 ANN Model (MLP) Test Results for A(t) of WWT

Sr. No.	Outage Hours (ANN Input)	Availability A(t)		Error (Absolute value)
		Desired Output	ANN Output (MLP)	
1.	24.20	0.9975	0.9931	0.0044
2.	305.50	0.9610	0.9570	0.0040
3.	214.10	0.9740	0.9780	0.0040
4.	1636.50	0.7800	0.8015	0.0215
5.	100.00	0.9820	0.9903	0.0083

As the error approaches zero, hence it is proved that the results of proposed ANN model are in good agreement with desired/actual results of availability. The ANN results are also compared graphically with the actual results and are shown in Fig. 4 justifying the good agreement between the two. Fig. 5 shows the magnitude of error between desired and simulated (ANN) values of availability.

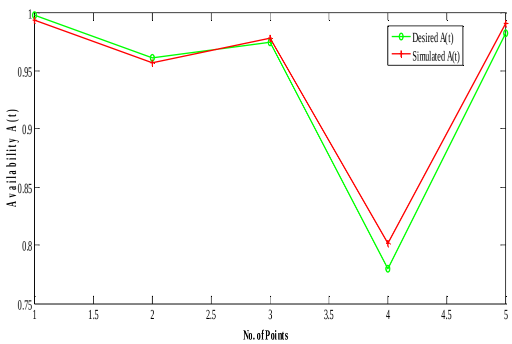


Fig. 4. Comparison of Desired and ANN Results of A(t)

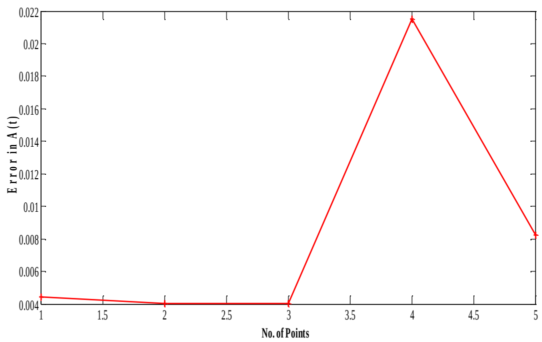


Fig. 5. Error in Values of A(t)

Table 3 gives the comparison of desired output and ANN output (RBF network) for R(t) of WWT and also shows the absolute value of error between the two.

Table 3 ANN Model (RBF) Test Results for R(t) of WWT

Sr. No.	Outage Hours (ANN Input)	Reliability R(t)		Error (Absolute value)
		Desired Output	ANN Output (RBF)	
1.	24.20	0.9972	0.9940	0.0032
2.	305.50	0.6830	0.6700	0.0130
3.	214.10	0.8622	0.9021	0.0399
4.	1636.50	0.0061	0.0092	0.0031
5.	100.00	0.9580	0.9785	0.0205

Table 4 show the absolute value of error between desired output and ANN output (RBF network) for different values of A(t) for WWT.

Table 4 ANN Model (RBF) Test Results for A(t) of WWT

Sr. No.	Outage Hours (ANN Input)	Availability A(t)		Error (Absolute value)
		Desired Output	ANN Output (RBF)	
1.	24.20	0.9975	0.9910	0.0065
2.	305.50	0.9610	0.9550	0.0060
3.	214.10	0.9740	0.9810	0.0070
4.	1636.50	0.7800	0.8035	0.0225
5.	100.00	0.9820	0.9914	0.0094

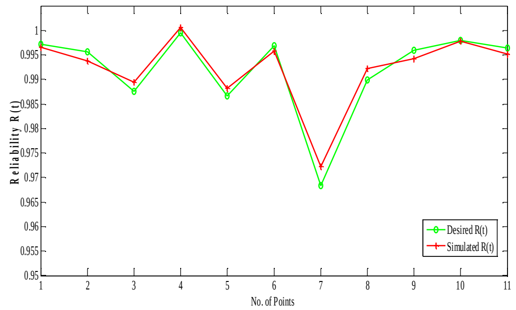
The MLP network produced a more fitted output than the RBF network this is evident from absolute values of error found by both the networks tabulated above. Network testing showed that both ANNs had similar strength in sediment load simulation. Therefore, the application of the MLP network using the testing data set resulted in lesser amounts of the mean square error, as compared to the RBF network.

Similarly the ANN model has been trained for known dataset of outage hours of all the components and respective value of R(t) and A(t). Once trained, this model is capable of finding R(t) and A(t) for new value of outage hours. Table 5 shows the test results of ANN model for R(t) with cumulative outage hours of various components as input to the model. The model has been found to be trained upto the precision of 10^{-4} and output when compared with actual or desired output shows almost negligible error.

Table 5 ANN Model Test Results using Cumulative Outage Data for R(t)

Sr. No.	Outage Hours (ANN Input)	Reliability R(t)		Error (Absolute value)
		Desired Output	ANN Output	
1.	24.42	0.9972	0.9966	0.0006
2.	37.83	0.9957	0.9937	0.0020
3.	54.64	0.9875	0.9895	0.0020
4.	2.0	0.9995	1	0.0011
5.	58.71	0.9866	0.9883	0.0017
6.	28.38	0.9968	0.9958	0.0010
7.	92.66	0.9684	0.9723	0.0039
8.	44.45	0.9899	0.9922	0.0023
9.	35.91	0.9959	0.9942	0.0017
10.	17.71	0.9980	0.9979	0.0001
11.	31.66	0.9964	0.9951	0.0013

The ANN results are compared graphically with the actual results and are shown in Fig. 6 justifying the good agreement between the two. Fig. 7 shows the magnitude of error between desired and simulated (ANN) values of reliability for this case.



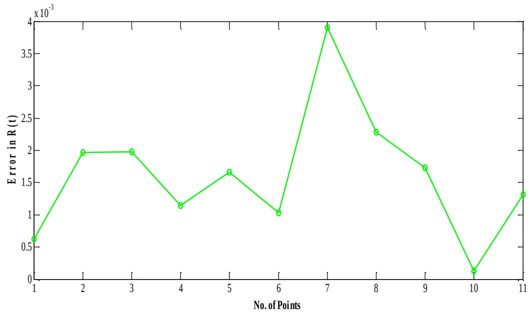


Fig.6. Comparison of Desired and ANN Results from Cumulative Data of R(t)

Fig.7. Error in Cumulative Values of R(t)

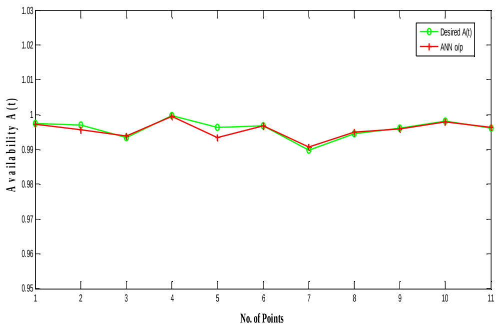
Table 6 shows the test results of ANN model for A(t) with cumulative outage hours of various components as input to the model.

Table 6 ANN Model Test Results using Cumulative Outage Data for A(t)

Sr. No.	Outage Hours (ANN Input)	Availability A(t)		Error (Absolute value)
		Desired Output	ANN Output	
1.	24.42	0.9974	0.9972	0.0002
2.	37.83	0.9969	0.9957	0.0012
3.	54.64	0.9934	0.9939	0.0005
4.	2.0	0.9998	0.9995	0.0003
5.	58.71	0.9963	0.9935	0.0028
6.	28.38	0.9968	0.9967	0.0001
7.	92.66	0.9897	0.9906	0.0009
8.	44.45	0.9946	0.9950	0.0004
9.	35.91	0.9960	0.9959	0.0001
10.	17.71	0.9980	0.9979	0.0001
11.	31.66	0.9960	0.9964	0.0004

The model has been found to be trained upto the precision of 10^{-4} and output when compared with actual or desired output shows almost negligible error.

The ANN results are also compared graphically with the actual results and are shown in Fig. 8 justifying the good agreement between the two. Fig. 9 shows the magnitude of error between desired and ANN simulated values of availability for this case.



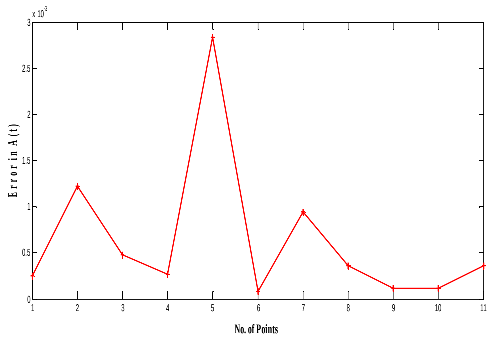


Fig. 8.Comparison of Desired and ANN Results from Cumulative Data of A(t)

Fig. 9. Error in Cumulative Values of A(t)

The reliability and availability have been also predicted using RBF network also for cumulative data set. Same observation has been made regarding absolute value of error i.e. MLP network gave more accurate values as compared to RBF.

Results and Discussions

A successful ANN model has been designed to predict the values of R(t) & A(t) it has been confirmed that there is no significant difference between desired and ANN output. The A(t) tends to increase after implementation of RCM decision logic, the value of which can be forecasted. The Table 8.8 presents the predicted results of enhanced availability after application of RCM. Post RCM, WWT showed 30% reduction in outage hours so this percentage reduction has been taken for other components also while giving input to ANN model for prediction [10,11]. These models successfully give output even without knowing the other parameter i.e. no. of failures. For next years 10% further reduction in outage has been considered. It is beneficial in a way that presently improved values of A(t) and R(t) of all components are not known, however using ANN model it can be made possible with great deal of accuracy. The results are strong convincing factor for maintenance department to implement RCM for availability improvements.

Tables 7 and Table 8 give the number of failures and respective outage time of selected components for all the four units. These are the parameters collected for the span of one year pre RCM.

Table 7 Parameters Collected from Unit-I and II (Pre RCM)

Component	Unit-I		Unit-II	
	No. of failures	Outage hours	No. of failures	Outage hours
WWT	27	1219.02	4	199.28
ECO	0	0	1	37.83
TURBINE	1	7.58	5	537.31
SH	0	0	3	169.7
RH	1	35.08	0	0
COND	1	31.66	1	24.42

Table 8 Parameters Collected from Unit-III and IV (Pre RCM)

Component	Unit-III		Unit-IV	
	No. of failures	Outage hours	No. of failures	Outage hours
WWT	1	44.45	24	1894.93
ECO	2	46.4	3	92.66
TURBINE	0	0	0	0
SH	3	104.2	0	0
RH	0	0	4	119.15
COND	0	0	1	28.38

Table 9 Availability Pre and Post RCM

Component	Total		MTBF	MTTR	Availability	30% reduced outage	Predicted Availability(After RCM)	10% further reduced outage	Predicted Availability(After RCM)
	No. of failure	Outage hours	Operating hours/Failures	Outage time/Failures	$\frac{MTBF}{MTBF + MTTR}$				
WWT	56	3357.68	96.47	59.95	0.617	2350.38	0.781	2115.34	0.784
ECO	6	176.89	1430.52	29.48	0.979	123.82	0.989	111.44	0.990
TURBINE	6	544.89	1369.19	90.81	0.937	381.42	0.957	343.28	0.961
SH	6	273.90	1414.35	45.65	0.969	191.73	0.986	172.55	0.989
RH	5	154.23	1721.15	30.85	0.982	107.96	0.989	97.16	0.990
COND	3	84.46	2891.85	28.15	0.990	59.12	0.993	53.21	0.994

Table 10 Reliability Pre and Post RCM

Component	Total		MTBF	Reliability	30% reduced outage	Predicted reliability(After RCM)	10% further reduced outage	Predicted reliability(After RCM)
	No. of failures	Outage hours	Operating hours/Failures	$e^{-(t/MTBF)}$				
WWT	56	3357.68	96.47	7.66E-16	2350.38	0.0011	2115.34	0.0012
ECO	6	176.89	1430.52	0.883	123.82	0.945	111.44	0.957
TURBINE	6	544.89	1369.19	0.672	381.42	0.856	343.28	0.895
SH	6	273.90	1414.35	0.824	191.73	0.904	172.55	0.914
RH	5	154.23	1721.15	0.914	107.96	0.960	97.16	0.970
COND	3	84.46	2891.85	0.971	59.12	0.988	53.21	0.989

Tables 9 and Table 10 show the total number of failures and outage time for the plant. Calculated values of MTBF, MTTR, availability and reliability are shown along with. The predicted values of availability and reliability have also been mentioned in these tables post RCM.

Conclusion

ANN model is successfully designed and results of this model are in good agreement with actual results. The expected benefits of RCM in terms of enhanced A(t) and R(t) can be foreseen using the model. The MLP network and RBF network with back propagation algorithm have been used as training function. The MLP network has been found to be best suited for parameter predictions in this study.

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