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Radial Basis Neural Network for Availability Analysis

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ABSTRACT

The appliance of radial basis neural network is demostrated in this paper. The method applies failure and repair rate signals to learn the hidden relationship presented into the input pattern. Statistics of availability of several years is considered and collected from the management of concern plant. This data is considered to train and calidate the radial basis neural network (RBNN). Subsequently validated RBNN is used to estimate the availability of concern plant. The main objective of using neural network approach is that it's not require assumption, nor explicit coding of the problem and also not require the complete knowledge of interdependencies, only requirement is raw data of system functioning.

NOMENCLATURE

		Greek Symbols	
hj	Hidden unit factor		
S	Spread function	$\mu_j^{'}$	Weight vector
A	Result from RBNN	ϕ_j	Radial basis function
T	Actual result	σ_j	Normalization factor
R	Regression	λ_j	Failure rate of ith subsystem
		μ_j	Repair rate of ith subsystem

1. Introduction

ANN is an architect that changes its configuration based on available data that propagate through the network during the training period. In general ANN used to develop complex relations between inputs and outputs data. In this work, RBNN is used. (Powell, Mason and Cox 1987) used Radial basis functions to solve the real multivariate problem. Radial basis functions were firstly combined with the field of neural network (Broomhead and Lowe 1988). Input into radial basis networks are nonlinear while the output is linear. Their admirable approximation abilities are studied in (Park and Sandberg 1991), (Poggio and Girosi 1990). Various functions have been tested as activation functions for RBF networks (Chen, Cowan and Grant 1991). Researcher used RBNN to solve problems where the input data are degraded with noise (Venkatesan and Anithe 2016). (Hartman, Keeler and Kowalski 1990) showed that ANN with a layer of hidden units of gaussian kind is a global approximator for real-valued function. Various researcher used various techniques for availability analysis. (Kumar, Singh and Pandey 1990) carried out reliability analysis of refining unit in sugar plant by using supplementary variable technique (SVT) (Dyer 1989), derived the solution of system state equation which depends on the eigen values of the model transition rate matrix. (Aven 1990) presented approximation formulations for the accessibility of standby redundant units including similar units. (Singh, Tewari and Khare 1991) discussed availability of conveyor belt system by using laplace transform and the generating function technique. (Singh and Dayal 1992) developed a reliability model to calculate reliability by using direct integration method. (Kaushik and Singh 1994) presented the reliability estimation of thermal power plant by using the laplace transform technique. (Singh and Goel 1995) developed a model of a series system composed of four subsystems having one standby sub unit with an imperfect switching. (Kumar, Mehta and Kumar 1997) presented the steady state analysis and maintenance order of the sub unit of fertilizer industry. (Arora and Kumar 1997) discussed the availability analysis of a steam generation system and derive the expression for steady state availability by using laplace transform

technique. (Gupta, Lal, Sharma and Singh 2005) calculated reliability, long run availability and mean time before failure of the cement manufacturing plant. (Gupta, Lal, Sharma and Singh 2007) calculate reliability of serial processes of plastic pipe manufacturing plant using matrix method and runga-kutta method. (Tewari, Kumar, Kajal and Khanduja 2015) drive the expression for steady state availability of crystallization unit of a sugar plant. (Garg, Kajal, Singh and Kumar 2008, Garg and Kumar 2009) discussed the steady state availability of screw plant and cattle feed plant using markov modeling. (Garg and Kumar 2009, Garg, Kajal, Singh and Kumar 2009, Garg, Singh, and Kumar 2009) evaluated the availability of rice plant and cattle feed plant, screw plant using matrix method. (Garg and Kumar 2009, Garg, Singh and Kumar 2009) applied matlab-tool to evaluate the availability of screw plant and cattle feed plant. (Bhattacharya and Singh 2011) used RBF to predict and back propagation model to compare the performance. (Mishra and Sharma 2018) applied ANN technique for analyse the rainfall time series. (Tatar, Naseri, Sirach, Moonyong and Bahadori 2015) used RBF neural networks with genetic algorithm for prediction. (Markopoulos, Georgiopoulos and Manolakos 2016) observed different kind of neural network to check performance and applicability. But ANNs approach has many advantages over these models. No prior knowledge about system configuration is required in ANN. Using failure history as input, ANN develops its own internal architects from the failure data and estimate value of availability for different values of input. In this paper, to analyze an unknown mapping, RBNN approach is used i.e. availability function of tab manufacturing plant.

2. Materials and Method

A RBF network is an ANN that has an input, hidden and linear output layer. The transformation functions used in hidden layer are based on Gaussian distribution. In which output depends upon the distance from neuron's center. Gaussian type RBF was chosen since it gives smooth result with interpolation (Markopoulos, Georgiopoulos and Manolakos 2016).

Types of layers in RBF networks are:

Input layer – Input layer has one neuron for every variable. Each of neuron in the hidden layer is feeded the value by input neurons.

Hidden layer – The layer includes a variable no. of neurons and the training process optimises this. The weights (μ_j, σ_j) are determined directly from the training data. No learning is involved. Hidden unit output h_j is obtained by closeness of input x to an M dimensional parameter vector μj associated with the hidden unit 4,7. When presented with the x vector of input values from the input layer, the jth hidden unit applies

RBF ϕj (.) to the normalized radial distance $\dfrac{\left\| x - \mu_j \right\|}{\sigma_j}$ between the input vector $x = (x_1, x_2, \ldots x_M)^T$ and the weight vector $\mu_j = (\mu_{j1}, \mu_{j2}, \ldots x_m)^T$. Normalization factor σ_j decides the range of influence of the jth unit around its centre μ_j. The result from hidden layer is propagated to the output layer.

Output layer – The output of the kth unit in the output layer of the network is given by

$$y_k = \sum_{j=0}^{J} w_{kj} h_j$$

Where $h_j = \varphi_j \left(\left\| \dfrac{x - \mu_j}{\sigma_j} \right\| \right), j = 1, 2 \ldots, J$ and $h_0 = -1$ is the output of bias unit.

2.1 Training RBF Networks

The available data is 'm' labelled pair as {Xi Yi} that represents associated multivariate functional input and output values and same is used as training data set. On given training set, an error function is minimized by considering sum of squared error criterion function. Gradient descent method (GDM) was used to train the data. The training has the following parameters:

1. No. of neurons in hidden layer.
2. The coordinates μ_j of the center of each hidden layer RBF function.
3. The σ_j of individual radial basis function in each dimension.
4. The weights applied to the RBF function outputs as they are passed to the output layer.

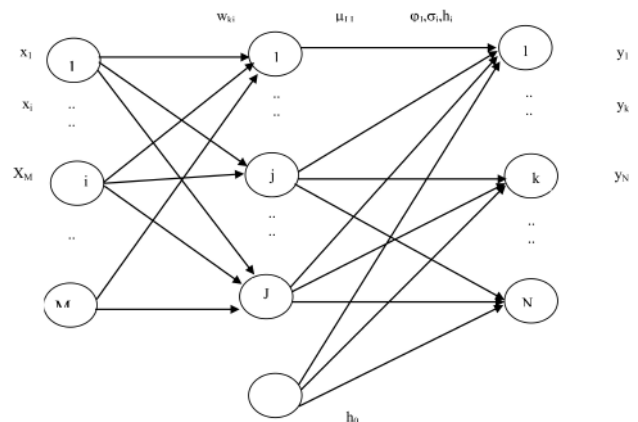K-means clustering is used to find cluster centers which are used as centers for radial basis functions.

Figure 1. The architecture of a radial basis function network [29]

2.2 *Identification of Input and Output Parameter*

As time permits, plant management apply complicated tests to reveal subtler defects. The aim of availability testing is find major problems with the different operating units timely. In Availability testing, operating system run for a planned period and investigator collect failure responses and repair periods, and compare the testing results to the planned objective.

Table 1. Variation of input parameter and corresponding variation of output parameter (Failure rates, Repair Rates) (Sample Data).

S. No.	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	λ_8	μ_1	μ_2	μ_3	μ_4	μ_5	μ_6	μ_7	μ_8	Availability
1	0.001	0.005	0.003	0.003	0.0025	0.007	0.007	0.004	0.01	0.05	0.03	0.03	0.02	0.07	0.07	0.04	0.6908
2	0.003	0.005	0.003	0.003	0.0025	0.007	0.007	0.004	0.01	0.05	0.03	0.03	0.02	0.07	0.07	0.04	0.6069
3	0.001	0.01	0.003	0.003	0.0025	0.007	0.007	0.004	0.01	0.05	0.03	0.03	0.02	0.07	0.07	0.04	0.6461
4	0.001	0.005	0.005	0.005	0.0025	0.007	0.007	0.004	0.01	0.05	0.03	0.03	0.02	0.07	0.07	0.04	0.6885
5	0.001	0.005	0.005	0.005	0.0025	0.007	0.007	0.004	0.01	0.05	0.09	0.09	0.02	0.07	0.07	0.04	0.6931
6	0.001	0.005	0.003	0.003	0.005	0.007	0.007	0.004	0.01	0.05	0.03	0.03	0.02	0.07	0.07	0.04	0.6359
7	0.001	0.005	0.003	0.003	0.0025	0.011	0.011	0.004	0.01	0.05	0.03	0.03	0.02	0.07	0.07	0.04	0.688
8	0.001	0.005	0.003	0.003	0.0025	0.011	0.011	0.004	0.01	0.05	0.03	0.03	0.02	0.14	0.14	0.04	0.6915
9	0.001	0.005	0.003	0.003	0.0025	0.007	0.007	0.008	0.01	0.05	0.03	0.03	0.02	0.07	0.07	0.04	0.6461
10	0.001	0.005	0.003	0.003	0.0025	0.007	0.007	0.016	0.01	0.05	0.03	0.03	0.02	0.07	0.07	0.1	0.6633
11	0.001	0.005	0.003	0.003	0.0025	0.007	0.007	0.032	0.01	0.05	0.03	0.03	0.02	0.07	0.07	0.04	0.4656
12	0.001	0.005	0.003	0.003	0.0025	0.007	0.007	0.032	0.01	0.05	0.03	0.03	0.02	0.07	0.07	0.06	0.5316
13	0.001	0.005	0.003	0.003	0.0025	0.007	0.007	0.032	0.01	0.05	0.03	0.03	0.02	0.07	0.07	0.08	0.5722
14	0.001	0.005	0.003	0.003	0.0025	0.007	0.007	0.016	0.01	0.05	0.03	0.03	0.02	0.07	0.07	0.06	0.6194
15	0.001	0.005	0.003	0.003	0.0025	0.007	0.007	0.016	0.01	0.05	0.03	0.03	0.02	0.07	0.07	0.08	0.6461
16	0.001	0.005	0.003	0.003	0.0025	0.007	0.007	0.004	0.02	0.05	0.03	0.03	0.02	0.07	0.07	0.04	0.7155
17	0.001	0.005	0.003	0.003	0.0025	0.007	0.007	0.004	0.01	0.07	0.03	0.03	0.02	0.07	0.07	0.04	0.7047
18	0.001	0.005	0.003	0.003	0.0025	0.007	0.007	0.004	0.01	0.05	0.09	0.09	0.02	0.07	0.07	0.04	0.6941
19	0.001	0.005	0.003	0.003	0.0025	0.007	0.007	0.004	0.01	0.05	0.03	0.03	0.05	0.07	0.07	0.04	0.7285
20	0.001	0.005	0.003	0.003	0.0025	0.007	0.007	0.004	0.01	0.05	0.03	0.03	0.02	0.14	0.14	0.04	0.6923
21	0.001	0.005	0.003	0.003	0.0025	0.007	0.007	0.004	0.01	0.05	0.03	0.03	0.02	0.07	0.07	0.06	0.707
22	0.001	0.005	0.003	0.003	0.0025	0.007	0.007	0.008	0.01	0.05	0.03	0.03	0.02	0.07	0.07	0.06	0.6752
23	0.001	0.005	0.003	0.003	0.0025	0.007	0.007	0.008	0.01	0.05	0.03	0.03	0.02	0.07	0.07	0.08	0.6908
24	0.001	0.005	0.003	0.003	0.0025	0.007	0.007	0.008	0.01	0.05	0.03	0.03	0.02	0.07	0.07	0.1	0.7004
25	0.001	0.005	0.003	0.003	0.0025	0.007	0.007	0.016	0.01	0.05	0.03	0.03	0.02	0.07	0.07	0.04	0.5722

3. Result and Discussion

Considering the different value for spread, value of availability obtained from radial basis neural network is given in table 2,3,4,5

Table 2. Result from RBNN for spread = 0.75

λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	λ_8	μ_1	μ_2	μ_3	μ_4	μ_5	μ_6	μ_7	μ_8	A	T
0.003	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.01	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.6074**	**0.6069**
0.003	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.02	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.6698**	**0.6677**
0.003	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.03	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.7005**	**0.6908**
0.001	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.01	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.6816**	**0.6908**

λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	λ_8	μ_1	μ_2	μ_3	μ_4	μ_5	μ_6	μ_7	μ_8	A	T
0.001	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.02	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.7314**	**0.7155**
0.001	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.03	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.7493**	**0.7241**
0.001	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.04	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.7354**	**0.7285**

Management of pharmaceutical provided availability testing results comprises of different values of failures and repair parameters of eight subsystem and corresponding value of availability of tab manufacturing plant. All this data is used for training and validation of the ANNs. Some of sample figures are given below in table 1. Sample data comprises of 16 input parameter (failure and repair rates of various eight subsystems) and one output parameter (availability).

Table 3. Result from RBNN for spread=1

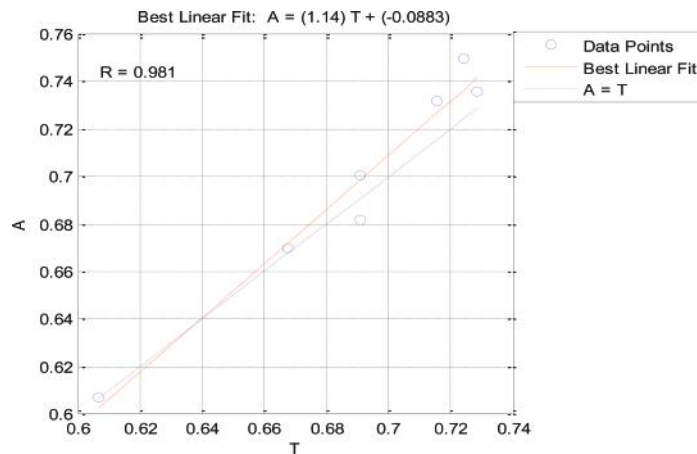| λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	λ_8	μ_1	μ_2	μ_3	μ_4	μ_5	μ_6	μ_7	μ_8	A	T
0.003	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.01	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.6203**	**0.6069**
0.003	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.02	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.6861**	**0.6677**
0.003	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.03	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.7226**	**0.6908**
0.001	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.01	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.6731**	**0.6908**
0.001	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.02	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.7389**	**0.7155**
0.001	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.03	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.7754**	**0.7241**
0.001	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.04	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.7825**	**0.7285**

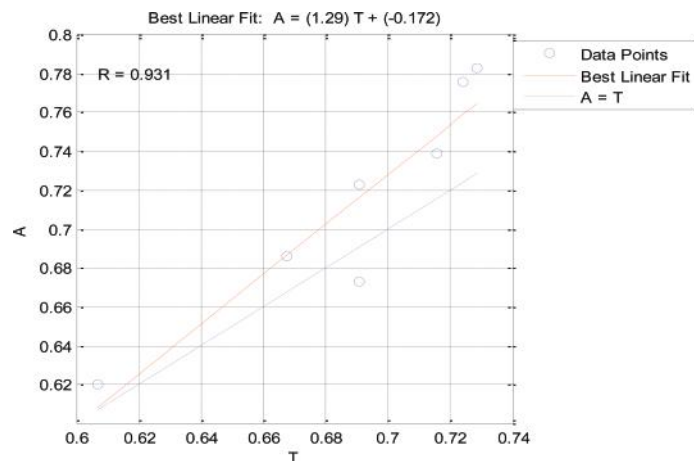**Figure 2**. Regression between actual result (A) and target result (T) for spread= 0.75

Figure 3. Regression model for actual result (A) and target result (T) for spread=1

Table 4. Result from RBNN for spread=1.50

λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	λ_8	μ_1	μ_2	μ_3	μ_4	μ_5	μ_6	μ_7	μ_8	A	T
0.003	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.01	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.6203**	**0.6069**
0.003	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.02	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.6861**	**0.6677**
0.003	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.03	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.7226**	**0.6908**
0.001	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.01	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.6731**	**0.6908**
0.001	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.02	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.7389**	**0.7155**
0.001	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.03	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.7754**	**0.7241**
0.001	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.04	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.7825**	**0.7285**

Table 5. Result from RBNN for spread=1.25

| λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	λ_8	μ_1	μ_2	μ_3	μ_4	μ_5	μ_6	μ_7	μ_8	A	T
0.003	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.01	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.6158**	**0.6069**
0.003	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.02	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.6814**	**0.6677**
0.003	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.03	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.7182**	**0.6908**
0.001	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.01	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.6687**	**0.6908**
0.001	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.02	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.7333**	**0.7155**
0.001	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.03	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.7690**	**0.7241**
0.001	0.005	0.003	0.003	0.025	0.007	0.007	0.004	0.04	0.05	0.03	0.03	0.02	0.07	0.07	0.04	**0.7758**	**0.7285**
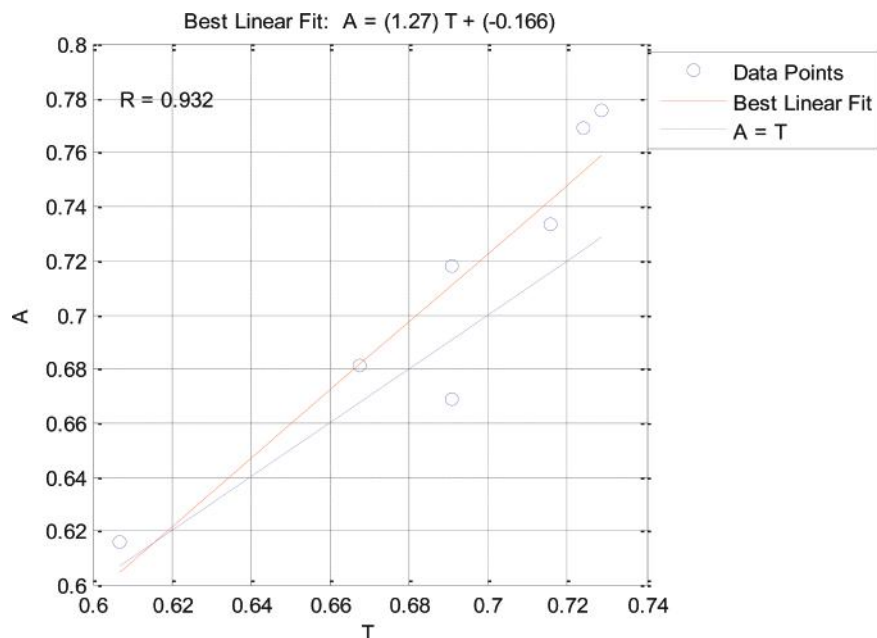
Figure 4. Regression model for actual result (A) and target result (T) for spread=1.5

Table 6. Regression coefficient for different spreads

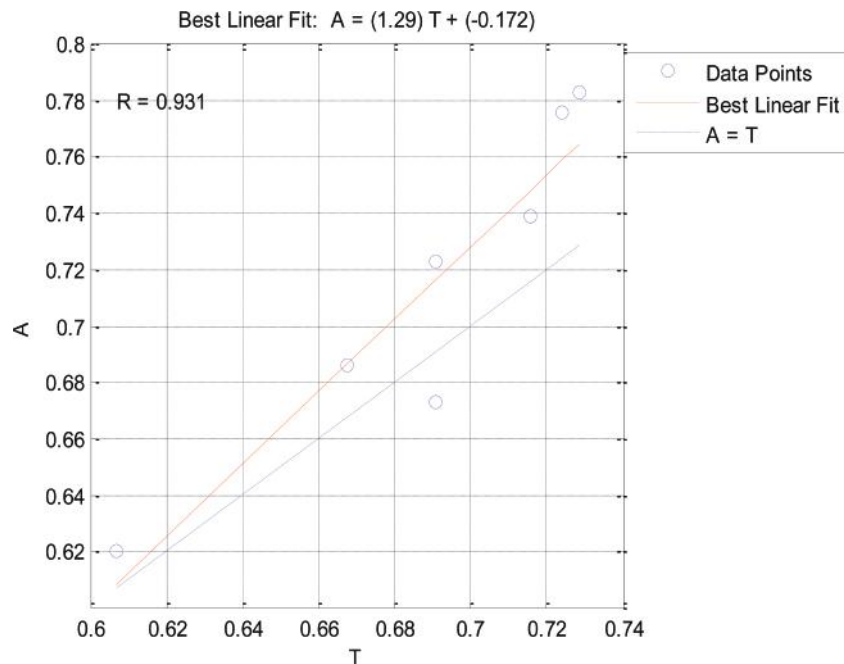| Spread	0.75	1	1.5	1.25
Regression coefficient	0.981	0.931	0.932	0.931

Figure 5. Regression model for actual result (A) and target result (T) for spread=1.25

Maximum value of regression (R) = 0.981, which is corresponding to spread function (S) = 0.75. So above experiment give better result for spread function (S) = 0.75.

Conclusion

Radial basis neural network has been used to approximate an unknown mapping. Historical data on the operation and failure of the system is collected over a sufficiently long period of time. With the help of this data, radial basis neural network is trained and validated. Failure and repair rates of eight subsystems are considered as the input of neural network. System availability is chosen as output parameter. With the help of validated neural network value of availability corresponding to different values of repair and failure rates of different subsystems are calculated. The procedural steps for the construction of an ANN have been delineated. Furthermore by using proposed network, effect of variation in failure and repair rates on the value of availability is also studied; so that value of failure and repair rates of various subsystems can be maintained at require level to achieve higher availability so as to avoid loss of production, loss of man power, complete breakdown of concern system.

Application of radial basis neural network approach in various research areas is extremely useful as no explicit coding of the problem is required. In present problem, availability analysis of tab manufacturing plant with help of neural network is significant, as no assumption, no complete knowledge of system configuration is required. Only raw data about failure, repair rates of various subsystems and corresponding value of availability is required. Furthermore if system configuration is known then also neural network approach is significant as systems are rarely simple, combination of series and parallel relationship and interdependencies between subsystems complicate the problem of determining overall system availability.

Acknowledgement

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