CHAPTER 8

CONCLUSIONS AND FUTURE SCOPE OF THE WORK

8.1 DISCUSSION ON THE PERFORMANCES OF ALGORITHMS

Table 8.1 presents the training parameters used in BPA/ RBF/ ESNN/ CMAC algorithms for weight updating of W1 and W2.

<table>
<thead>
<tr>
<th>ANN algorithm</th>
<th>Number of nodes in the input layer</th>
<th>Number of nodes/ centers/ reservoirs in the hidden layer</th>
<th>Number of nodes in the output layer</th>
<th>Number of iterations for convergence to reach MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>BPA</td>
<td>30 /32</td>
<td>Number of nodes =10</td>
<td>1</td>
<td>78</td>
</tr>
<tr>
<td>RBF</td>
<td>Stage 1: 30 / 32</td>
<td>Number of centers=10</td>
<td>Stage 1: Number of rules=10</td>
<td>Stage 2: Number of target output=1</td>
</tr>
<tr>
<td></td>
<td>Stage 2: Number of rules</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ESNN</td>
<td>30 /32</td>
<td>Number of reservoirs = number of rules=10</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>CMAC</td>
<td>30 /32</td>
<td>Number of nodes=10</td>
<td>1</td>
<td>103</td>
</tr>
</tbody>
</table>
Some of the training properties of BPA/ RBF/ ESNN/ CMAC algorithms are presented in Table 8.2. Each ANN algorithm is influenced by its activation function and the type of weight updating rules.

**Table 8.2 Training properties of BPA/ RBF/ ESNN/ CMAC**

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Weight forming mechanism</th>
<th>Stopping the training process</th>
<th>Final weights formation</th>
<th>Activation function used</th>
</tr>
</thead>
<tbody>
<tr>
<td>Backpropagation algorithm (BPA)</td>
<td>Feed forward for input–output mapping. Weight updating equation from output to input layer through hidden layer</td>
<td>Many iterations are required to reach a mean squared error criteria (MSE)</td>
<td>Initial weight matrices W1= input membership function, W2= defuzzification values</td>
<td>Sigmoid function</td>
</tr>
<tr>
<td>Radial basis function (RBF) with FL</td>
<td>Centers are decided. Distance between centers and the input patterns are found to create an RBF matrix</td>
<td>Only one iteration is required</td>
<td>The weight matrix is formed by multiplying RBF matrix with target outputs</td>
<td>Exponential function</td>
</tr>
<tr>
<td>Echo state neural network (ESNN)</td>
<td>Reservoirs in the hidden layer is fixed to obtain state vectors for all the input training patterns</td>
<td>Only one iteration is required</td>
<td>Initial weight matrices W1= input membership function, W2= defuzzification values. Weight matrix W for the reservoirs = initial random numbers. The final weight matrix is formed by multiplying state vector matrix with target outputs.</td>
<td>Tanh function</td>
</tr>
<tr>
<td>Cerebellar model articulation controller (CMAC)</td>
<td>Feed forward for input–output mapping. Weight updating equation from output to input layer through hidden layer. Apply quantization</td>
<td>Many iterations are required to reach a mean squared error criteria (MSE)</td>
<td>Initial weight matrices W1= input membership function, W2= defuzzification values</td>
<td>Sigmoid function</td>
</tr>
</tbody>
</table>
The categorization of SCD is presented in Table 8.3. The categorization is applied to decide if the manufacturing process is continuously working or it is disrupted based on the outputs of the FIS.

### Table 8.3 Description of categorization of SCD decision

<table>
<thead>
<tr>
<th>Category</th>
<th>FIS output</th>
<th>SCD</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class I</td>
<td>0.7-0.9</td>
<td>Not present</td>
<td>The manufacturing target can be reached without time delay.</td>
</tr>
<tr>
<td></td>
<td>0.5 &lt; 0.7</td>
<td>Not present</td>
<td>The manufacturing target can be reached with time delay.</td>
</tr>
<tr>
<td>Class II</td>
<td>&lt; 0.5</td>
<td>Present</td>
<td>There is a breakdown in manufacturing. Atleast one machine is not working or insufficient facilities and insufficient materials.</td>
</tr>
</tbody>
</table>

Table 8.4 presents the number of test input patterns that are classified into SCD or “NO SCD”.

### Table 8.4 Percentage error in classification

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Class-I No SCD</th>
<th>10% SCD</th>
<th>20% SCD</th>
<th>20-50% SCD</th>
<th>Number of patterns misclassified</th>
<th>Percentage error in classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>FIS</td>
<td>300</td>
<td>50</td>
<td>40</td>
<td>65</td>
<td>45</td>
<td>0.09</td>
</tr>
<tr>
<td>FIS parameters replaced with trained values obtained from BPA</td>
<td>300</td>
<td>42</td>
<td>43</td>
<td>80</td>
<td>35</td>
<td>0.07</td>
</tr>
<tr>
<td>FIS parameters replaced with trained values obtained from RBF</td>
<td>300</td>
<td>42</td>
<td>43</td>
<td>85</td>
<td>30</td>
<td>0.06</td>
</tr>
<tr>
<td>FIS parameters</td>
<td>300</td>
<td>50</td>
<td>50</td>
<td>90</td>
<td>10</td>
<td>0.02</td>
</tr>
</tbody>
</table>
are replaced with trained values obtained from ESNN
are replaced with trained values obtained from CMAC

| FIS parameters are replaced with trained values obtained from CMAC | 300 | 50  | 48  | 95  | 7   | 0.014 |

Figure 8.1 presents the percentage of error in classifying the test input patterns. The bar chart plotted is based on the percent error classification given in Table 7.4. The blue color bar shows the least error of 0.014 for the FIS trained with CMAC. The red color bar shows the highest error of 0.09 for FIS without updating its parameters by using BPA/ RBF/ ESNN/ CMAC.

![Error percentage from neuro-fuzzy algorithms](image)

**Figure 8.1** Error percentage from neuro-fuzzy algorithms

The performance of BPA/ RBF/ ESNN/ CMAC/ FIS is presented in Figure 8.2. All the algorithms show 100% performance when the data has
no SCD information. Performance changes among the algorithms, only when SCD information is present. The performance of RBF and BPA are only 84% when the SCD is 10%, whereas the performances of CMAC, ESNN and FIS are 100%. In case of 20% SCD, the performance of ESNN is 100%, the performance of CMAC is 96%, and the performance of remaining algorithms is less than 86%. When the SCD is 20% to 50%, the performance of CMAC is 95%, and the performance of the remaining algorithms is less than 90%.

![Performance of BPA/ RBF/ ESNN/ CMAC/ FIS](image)

**Figure 8.2 Performance of BPA/ RBF/ ESNN/ CMAC/ FIS**

### 8.2 RECEIVER OPERATING CHARACTERISTICS (ROC)

Receiver Operating Characteristic (ROC) curves are very much used in the performance evaluation of artificial neural network and fuzzy logic algorithms. The different points on the ROC curve indicate the performance of the algorithms for different sets of data. In this work, 1000 patterns of data have been obtained from company records. One point in the ROC is obtained by testing the algorithms by using remaining nine points in the ROC, (the set-2
data) is modified nine different times. Hence, additional 9 points in the ROC is obtained. The modifications of the data are done randomly.

The ROC curve provides information on the tradeoff between the hit rate (true positives) and the false alarm rates (false positives). To draw the ROC curve both positive (fault) and negative (no-fault) examples are needed.

ROC curve is drawn using a set of positive and negative examples.

i) **True positive:** -If the data contains information about a defect in one of the machines/ no material/ no facility, and if the proposed algorithms detect the presence of a defect/ no material/ no facility, then it is trulypositive,

ii) **False negative:** - If the data contains information about a defect in one of the machines/ no material/ no facility and if the proposed algorithms do not detect the presence of a defect/ no material/ no facility, then it is false negative,

iii) **True negative:** If the data contain information like good working condition of machine / presence of material/ presence of working facility and if the algorithms indicate good working condition of machine / presence of material/ presence of working facility, then it is trulynegative, and,

iv) **False positive:** If the data contain information like good working condition of machine / presence of material/ presence of working facility and if the proposed algorithm says defect/ no material/ no facility, then it is false positive.
8.3 ACCURACY OF SCD DETECTION

The accuracy refers to how correctly, the BPA/ RBF/ ESNN/ CMAC can train the FIS to identify the presence of defect in one of the machines/ no material/ no facility in the manufacturing line. The detection rate is computed using the equation 8.1 and 8.2.

\[
Sensitivity = \frac{TP}{TP + FN} \quad (8.1) \\
Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (8.2)
\]

Where
FP—False Positive,
FN—False Negative,
TP—True Positive, and
TN—True Negative.

The sensitivity represents the amount of true positive (detecting the presence of a defect in one of the machines/ no material/ no facility from the test patterns). Higher the sensitivity value, the BPA/ RBF/ ESNN/ CMAC/ FIS is good in detecting a defect in one of the machines/ no material/ no facility.

The accuracy represents the correct identification of the test patterns having presence of a defect in one of the machines/ no material/ no facility and good working condition of machine / presence of material/ presence of working facility. Higher the accuracy value, higher is the performance of the BPA/ RBF/ ESNN/ CMAC/ FIS.
Figure 8.3  ROC for BPA for SCD estimation

Figure 8.3 shows ten points. Each point represents 30 patterns from set-2 test patterns. All the points are above the diagonal (0,0 and 1,1). When the points are above the diagonal, they indicate that BPA identifies the presence of a defect in one of the machines/ no material/ no facility and good working condition of machine / presence of material/ presence of working facility correctly. The range of TPR value is 0.87 to 0.96, and the range of FPR value is 0.01 to 0.06.

Figure 8.4  ROC for RBF for SCD estimation
Figure 8.4 shows ten points. Each point represents 30 patterns from set-2 test patterns. All the points are above the diagonal (0,0 and 1,1). When the points are above the diagonal, they indicate that RBF identifies the presence of a defect in one of the machines/ no material/ no facility and good working condition of machine / presence of material/ presence of working facility correctly. The range of TPR value is 0.87 to 0.96, and the range of FPR value is 0.02 to 0.14.

Figure 8.5  ROC for ESNN algorithm for SCD estimation

Figure 8.5 shows ten points. Each point represents one (set-2 test patterns). All the points are above the diagonal (0,0 and 1,1). When the points are above the diagonal, they indicate that ESNN identifies the presence of a defect in one of the machines/ no material/ no facility and good working condition of machine / presence of material/ presence of working facility correctly. The range of TPR value is 0.87 to 0.96, and the range of FPR value is 0.02 to 0.1.
Figure 8.6  ROC for CMAC algorithm for SCD estimation

Figure 8.6 shows ten points. Each point represents 30 patterns from set-2 test patterns. All the points are above the diagonal (0,0 and 1,1). When the points are above the diagonal, they indicate that CMAC identifies presence of a defect in one of the machines/ no material/ no facility and good working condition of machine / presence of material/ presence of working facility correctly. The range of TPR value is 0.87 to 0.95, and the range of FPR value is 0.01 to 0.05.

Figure 8.7  Accuracy of BPA/ RBF/ ESNN/ CMAC algorithms
Figure 8.7 presents bar chart comparing the accuracies of the implemented neuro-fuzzy algorithms for ten different pattern (set-2 test patterns). ESNN provides the highest accuracy when compared to other three algorithms in all the ten testings. The accuracy varies between 88.235% and 97.59%. The accuracy of BPA is the least in all the testings. The difference in the accuracies of the four algorithms is wide in range and consistent during testings (1, 3, 4, 8, 9, 10). Similarly, the difference in the accuracies of the four algorithms is very close during testings (2, 5, 6, 7).

Figure 8.8 Sensitivity of BPA/ RBF/ ESNN/ CMAC algorithms

Figure 8.8 presents bar chart comparing the sensitivities of the implemented neuro-fuzzy algorithms for ten different (set-2 test patterns). The average sensitivity of BPA=90.416%, RBF=89.916%, CMAC=89.66%, and ESNN=90.916%. BPA is more sensitive to changes in the patterns whereas RBF (preferable) is less sensitive to changes in the patterns.

Facility location and a case study has been carried out. The fuzzy algorithms are implemented and the minimum travelling cost obtained is 126.16 units. The possible path of minimum travelling distance obtained in the
location V7-V2-V5-V3-V4-V10-V7-V8-V6-V1. The hypothetical problem deals with facility location problem with fuzzy decision making. It is assumed in beverage plant and distributor network. Comparison results show that, BPA algorithm produced better solution than other fuzzy algorithms.

8.4 CONCLUSION

Estimation of the supply chain disruption in a fastener/ automobile/ paper manufacturing factory is presented. The working status of various facilities in the factory is collected and converted into numerical values to form patterns. These patterns are used to train and test the neuro-fuzzy methods. The proposed methods are superior to existing methods in such a way that they could estimate the status of SCD even if there is a loss of data partially or if few inputs are given with slight changes. The proposed methods are different in the sense that they can earn a huge amount of patterns obtained from the factory for estimating the SCD. The methods provide newer directions for the actual usage of neuro-fuzzy methods in the SCD estimation. The methods have multifold advantages. The advantages are:

i) ESNN is a recurrent algorithm. The internal nodes (reservoirs) of the ESNN stores different states of the SCD and NO SCD patterns during training. This state in a combination of the FL provides the best estimation of the amount SCD.

ii) BPA learns the patterns with repeated iterations. It converges globally when the alpha, beta parameters are correctly set. Hence, this algorithm can learn SCD data. If time is not a constraint, then BPA + FL can be used for SCD estimation.

iii) CMAC learns patterns by quantizing the input values. These values are stored in different input spaces. Due to the storage of patterns in
different spaces, the learning capability of CMAC increases and hence its association properties of inputs-outputs.

iv) RBF learns all the SCD patterns in one iteration. It is the advantage of RBF. When a correct number of centers are decided in RBF, then FIS+RBF will be suitable for SCD estimation. All the proposed neuro-fuzzy algorithms perform best in estimating no SCD condition. However, when the fault in the number of the machine increases, the performance of the proposed algorithms varies. As a future work, the proposed algorithms can be extended to the factory with some machines and more manufacturing constraints involved.

v) BPA algorithm produced better than other neural network algorithms for supply network allocation problems.

Earlier works on SCD management used linear programming, fuzzy logic, genetic algorithm and neural networks. The neuro-fuzzy methods provide better advantages over other existing methods regarding quicker learning and the estimation of the SCD with less error. Any company can use the proposed algorithms to customize for their manufacturing environment.