8.1 Introduction

Various hybrid systems that fuse Fuzzy control and Neural networks have been propounded [1, 106]. Hahn-ming Lee and Bing-Hui Lu [57] proposed an NN model with fuzzy inference based on the Backpropagation learning algorithm (Fuzzy BP). Lee and Lu used conventional Backpropagation with gradient descent method for weight determination.

GAs on the other hand, have been used to design efficient training algorithms for Neural networks. Such a GA based learning algorithm for the Fuzzy BP model proposed by Lee and Lu is discussed in this chapter. A GA has been employed for weight determination so as to minimize the error. The algorithm proposed employs real coded chromosomes and Matrix Cross Over operator for reproduction.

The Fuzzy BP model and its governing learning equations are discussed first, before the GA based Fuzzy BP model (GA-Fuzzy BP) is presented. The performance of the two networks has been compared over an experimental problem in Structural Engineering, viz., that of determining the allowable stress limits of a beam subjected to lateral loads, and for the evaluation of earthquake damage on structures situated at different distances from the epicenter.
8.2 Fuzzy BP model

The Fuzzy BP is a three-layered Feedforward network. The inputs to the Fuzzy BP network are represented as LR type fuzzy numbers as proposed by Dubois and Prade [18]. An LR type fuzzy number has been defined in Chapter 5. However, an alternative definition is presented below:

A fuzzy number $\tilde{M}$ is said to be an LR type fuzzy number iff

$$
\mu_{\tilde{M}} = \begin{cases} 
L \left( \frac{(m-x)}{\alpha} \right) & \text{for } x < m, \alpha > 0 = \max(0,1 - \frac{(m-x)}{\alpha}) \\
R \left( \frac{(x-m)}{\beta} \right) & \text{for } x \geq m, \beta > 0 = \max(0,1 - \frac{(x-m)}{\beta})
\end{cases} \tag{8.1}
$$

where $L$ and $R$ are the left and right reference functions respectively, $\mu_{\tilde{M}}$ is the membership function of fuzzy number $\tilde{M}$, $m$ the mean value of $\tilde{M}$, and $\alpha$ and $\beta$ are the left and right spreads respectively.

The basic operations of LR type Fuzzy numbers relevant to the investigation carried out, is given by,

**Addition:**

$$(m, \alpha, \beta)_{LR} + (n, \gamma, \delta)_{LR} = (m + n, \alpha + \gamma, \beta + \delta)_{LR}$$

**Multiplication:**

$$(m, \alpha, \beta)_{LR} \times (n, \gamma, \delta)_{LR} = \begin{cases} 
(mn, m\gamma + n\alpha, m\delta + n\beta)_{LR}, & m \geq 0, n \geq 0 \\
(mn, n\alpha - m\delta, n\beta - m\gamma)_{LR}, & m < 0, n \geq 0 \\
(mn, -n\beta - m\delta, -n\alpha + m\gamma)_{LR}, & m < 0, n < 0
\end{cases}$$

**Scalar Multiplication:**

$$\lambda \cdot (m, \alpha, \beta)_{LR} = \begin{cases} 
(\lambda m, \lambda \alpha, \lambda \beta)_{LR}, & \forall \lambda \geq 0, \lambda \in R \\
(\lambda m, -\lambda \alpha, -\lambda \beta)_{RL}, & \forall \lambda < 0, \lambda \in R
\end{cases} \tag{8.2-8.4}$$
8.2.1 Fuzzy Neuron

The Fuzzy Neuron is the basic element of Fuzzy BP. It performs nonlinear mapping between the weight summation of fuzzy input vectors and crisp outputs. Fig. 8.1 shows the structure of a Fuzzy Neuron.

Fuzzy number \( \tilde{I} = (\tilde{I}_0, \tilde{I}_1, \ldots, \tilde{I}_n) \) is the input vector and \( \tilde{W} = (\tilde{W}_1, \tilde{W}_2, \ldots, \tilde{W}_m) \) is the fuzzy weight vector where \( \tilde{I}_0 \) is the bias equal to \((1,0,0)\). The Fuzzy weighted summation \( \tilde{w}t = \sum_{i} \tilde{W}_i \tilde{I}_i \) and the inference result \( NET = CE(\tilde{w}t) \). CE is the centroid operation of a triangular fuzzy number and can be viewed as a defuzzification operation that maps fuzzy value to a crisp value.

8.2.2 Architecture of the Fuzzy BP model

In a fuzzy BP model (shown in Fig. 8.2), when an input vector \( \tilde{I}_p = (\tilde{I}_{p1}, \tilde{I}_{p2}, \ldots, \tilde{I}_{pl}) \) where each \( \tilde{I}_{pi} \) is an LR type fuzzy number, is presented to the input layer, the processing undertaken by each layer is given by:

Input Units: \( \tilde{O}_{pi} = \tilde{I}_{pi}, i = 1,2,\ldots,l \)
\( \tilde{O}_{p0} = (1,0,0) \) \hspace{1cm} (8.5)

Hidden Units: \( O'_{pj} = f(NET_{pj}) i = 1,2,\ldots,m \)
\( O'_{p0} = 1 \) \hspace{1cm} (8.6)

\( NET_{pj} = CE(\sum_{i=0}^{l} \tilde{W}_{ji} \tilde{O}_{pi}) \) \hspace{1cm} (8.7)

Output Units: \( O''_{pk} = f(NET''_{pk}) k = 0,1,2,\ldots,n \) \hspace{1cm} (8.8)
In the set of equations (8.5-8.9), \( \tilde{O}_{pi} \) is the output generated by the \( i \)th input node, and \( O'_{pj}, O''_{pk} \) are the \( j \)th and the \( k \)th crisp (defuzzified) outputs of the hidden and output nodes respectively, obtained using the centroid function,

\[
CE(\tilde{\eta}) = net_m + \frac{1}{3} (net_\beta - net_\alpha)
\]

\( = NET \)

and the sigmoidal function,

\[
f(NET) = \frac{1}{1 + e^{-NET}}
\]

Here, \( \tilde{\eta} \) is an LR type triangular fuzzy number \( (net_m, net_\alpha, net_\beta) \), where \( net_m \) is the mean value and \( net_\alpha \) and \( net_\beta \) are the left and right spreads respectively.

\( \tilde{W}_{ji} \) is the fuzzy connection weight between the \( i \)th input node and the \( j \)th hidden node, and \( \tilde{W}^{'}_{kj} \) is the fuzzy connection weight between the \( j \)th hidden node and the \( k \)th output node.

In the learning phase, the values of weights are adjusted to minimize the error

\[
E = \sum P_e \quad \text{where,} \quad E_p = \frac{1}{2} (D_{pi} - O''_{pi})^2
\]

\( D_{pi} \) is the desired output value of the \( i \)th output unit and \( O''_{pi} \) is the actual output value of the \( i \)th output unit, which is determined by the equation,

\[
\Delta \tilde{W}(t) = -\eta \nabla E_p(t) + \alpha \Delta \tilde{W}(t - 1)
\]
In this, $\eta$ is the learning rate, $\alpha$ is the momentum factor and $\nabla E_p(t)$ is given by

$$\nabla E_p(t) = \frac{\partial E_p}{\partial \tilde{W}(t)}$$

(8.14)

### 8.3 GA based Fuzzy BP

The fuzzy BP model determines its weights with the help of the weight updating equations (8.12-8.14). In the GA based Fuzzy BP model, these equations have been dispensed with, and a GA has been employed to determine the fuzzy weight vectors $\tilde{W}(t)$.

Before a GA is run, a suitable coding for the problem needs to be devised. The fitness function, which assigns merit to each of the individuals in the population, has to be formulated. During the run, parents must be selected for reproduction and crossed over to generate offspring. These aspects of the GA for the determination of the weight vectors for the Fuzzy BP model have been described below:

**Coding:** With fuzzy weight vectors $\tilde{W}(t)$ being real, adopting the real coded system has led to the direct determination of weights thereby avoiding the extra computation and conversion, the binary coded system calls for, in transforming the binary coded chromosomes to their actual values.

Assume a Fuzzy BP whose network configuration is $l - m - n$ (l input neurons, m hidden neurons and n output neurons). The number of weights that are to be determined are $(l + n)m$. With each weight being a real number and more so, an LR type triangular fuzzy number, and assuming the number of digits (string length) in the weight to be d, a string S of decimal values representing the $(l + n)m$ weights and therefore having a string length
\( L = (l + n)m.d^3 \), is randomly generated. The string \( S \) represents the weight matrices of the input-hidden and hidden-output layers, in a linear form, arranged according to row major or column major order as selected by the designer.

Let \( x_1, x_2, \ldots, x_d, \ldots, x_L \) represent a chromosome and \( x_{kd+1}, x_{kd+2}, \ldots, x_{(k+1)d} \) represent the \( k \)th gene in the chromosome coding a weight vector \( \tilde{W}_k \). The actual weight component \( w_{km} \), where \( \tilde{W}_k = (w_{km}, w_{k\alpha}, w_{k\beta}) \) is given by

\[
w_{km} = \begin{cases} 
\frac{(x_{kd+2}10^{d-1} + x_{kd+3}10^{d-2} \ldots x_{(k+1)d})}{10^{d-1}}, & \text{if } 5 \leq x_{kd+1} \leq 9 \\
\frac{(x_{kd+2}10^{d-1} + x_{kd+3}10^{d-2} \ldots x_{(k+1)d})}{10^{d-1}}, & \text{if } 0 \leq x_{kd+1} < 5
\end{cases}
\]

(8.15)

The initial population comprises of such randomly generated chromosomes.

**Fitness function:** The algorithm for the computation of the fitness function is illustrated below:

**ALGORITHM FUZ_BP_FITGEN()**

\{
Let \((\tilde{I}_i, \overline{I}_i), i = 1, 2, \ldots, N \) where \( \tilde{I}_i = (I_{1i}; I_{2i}; \ldots; I_{li}) \) and \( \overline{I}_i = (T_{1i}; T_{2i}; \ldots; T_{ni}) \) represent the LR type fuzzy number representations of the input output pairs of the problem to be solved by the GA based Fuzzy BP model with a configuration \( l - m - n \).

For each chromosome \( C_i, i = 1, 2, \ldots, p \) belonging to the current population \( P_i \) whose size is \( p \)
\{
Extract weights \( W_i \) from \( C_i \) with the help of result (8.15);
\}
Keeping $W_i$ as a fixed weight setting, train the network for the $N$ input instances;

Calculate error $E_i$ for each of the input instance using the formula,

$$E_i = \sum_j (T_{ji} - O_{ji})^2$$  \hspace{1cm} (8.16)

where $O_i$ is the output vector calculated by the GA based Fuzzy BP model;

Find the root mean square $E$ of the errors

$$E = \sqrt{\frac{\sum_i E_i}{N}}$$  \hspace{1cm} (8.17)

Calculate the fitness value $F_i$ for each of the individual string of the population as

$$F_i = \frac{1}{E}$$  \hspace{1cm} (8.18)

Output $F_i$ for each $C_i, i = 1,2, ..., p$.

END FUZ_BP_FITGEN.

Reproduction: In this phase, the mating pool is first formed before the parent chromosomes reproduce to deliver offspring with better fitness. For the given problem, the mating pool is first formed by excluding that chromosome $C_i^i$ with the least fitness $F_i^i$ and replacing it with a duplicate copy of the chromosome $C_i''$ reporting the highest fitness $F_i''$. Having formed the mating pool, the parents are selected in pairs at random. The chromosomes of the respective pairs are recombined using the two dimensional Matrix Cross Over Operator. The offspring, which now form
the current population again, have their fitness calculated as illustrated by algorithm \textit{FUZ\_BP\_FITGEN}()

\textbf{Convergence:} A population is said to have converged when 95\% of the individuals constituting the population share the same fitness value. A similar criterion has been used in the technique proposed.

Summing up, the algorithm for the GA based weight determination of Fuzzy BP is:

\begin{verbatim}
ALGORITHM GA\_FUZ\_BP\_WT()
{
  i ← 0;
  Generate the initial population \( P_i \) of real coded chromosomes \( C^i_j \) each representing a weight set for the GA based Fuzzy BP;

  While the current population \( P_i \) has not converged
  { Generate fitness values \( F^i_j \) for each \( C^i_j \in P^i \) using the algorithm \textit{FUZ\_BP\_FITGEN}();

    Get the mating pool ready by exchanging worst fit individuals and duplicating high fit individuals;

    Using the cross over mechanism reproduce offspring from the parent chromosomes;

    \( i ← i + 1; \)

    Call the current population \( P_i \);

    Calculate fitness values \( F^i_j \) for each \( C^i_j \in P^i \);
  }

  Extract weights from \( P_i \) to be used by the GA based Fuzzy BP;
}
END GA\_FUZ\_BP\_WT.
\end{verbatim}
The System flow and input/output specifications of the implementation of GA-Fuzzy BP architecture have been illustrated in Appendix E.

8.4 Application

In this section the application of the GA based Fuzzy BP model to two problems, viz.,

(i) Determination of allowable stress limits of a beam subject to lateral loads.

(ii) Evaluation of earthquake damage is discussed.

8.4.1 Allowable stress limits determination of a beam subject to lateral loads:

Bending stress is developed in a beam when it is subjected to lateral loads. A beam should be designed such that the stresses developed should not exceed the allowable stress limits. The allowable stress of a standard beam section (Equal flange-I sections or channels) depend mainly on slenderness ratio and $\frac{D}{T}$ ratio. Here, slenderness ratio is the length / minimum radius of gyration and $\frac{D}{T}$ is the overall depth/thickness of the compression flange. The allowable stress is governed by the following equation:

$$\sigma_{bc} = 0.66 \frac{f_{cb} f_g}{\left((f_{cb})^n + (f_y)^n\right)^{\frac{1}{n}}}$$

(8.19)
\( f_{cb} \): Elastic critical stress in bending \( \alpha \frac{D}{T} \) and \( \frac{l}{r_y} \) ratio

\( f_y \): Yield stress of steel

\( l \): length

\( r_y \): Minimum radius of gyration

\( \sigma_{bc} \): Allowable stress

Slenderness ratios and \( \frac{D}{T} \) ratios are represented in fuzzy form as illustrated in Fig. 8.3 and Fig. 8.4 respectively. Table 8.1 and Table 8.2 illustrate the fuzzy linguistic values associated with the slenderness and \( \frac{D}{T} \) ratios respectively. For each pair of fuzzy input values, viz., slenderness ratio and \( \frac{D}{T} \) ratio, a crisp output value, which is the corresponding permissible stress value (as given in Table 8.3), is associated.

Experiments have been carried out for both trained and untrained instances (inputs which the network had not seen earlier). Figs. 8.5 and 8.6 represent a comparison of the actual permissible stress value (normalized) with the value as calculated by the GA based fuzzy BP and the conventional Fuzzy BP model, respectively. The results have been presented for trained instances. Figs. 8.7 and 8.8 indicate results for untrained instances. The convergence history for the GA based Fuzzy BP model has been illustrated in Fig. 8.9.

\textbf{8.4.2 Earthquake Damage Evaluation}

Evaluation of earthquake damage is a complicated exercise as the problem involves manipulation of vague concepts. Damage characteristics
of a few kinds of structures situated at different distances from damage centers have been evaluated for the last 9 earthquakes in Japan [96]. Using expert knowledge, the amount of damages have been expressed in terms of a damage membership function. The inputs presented to the GA based Fuzzy BP model are, earthquake magnitude, epicentral distance and the ratio of the peak ground acceleration and spectrum intensity. The fuzzy linguistic values associated with the inputs have been illustrated in Table 8.4. The fuzzy form of the inputs has been presented in Figs. 8.10 (a, b, c). Table 8.5 illustrates the fuzzy inputs and the corresponding damage membership function (which is the output) for the 9 earthquakes.

Fig. 8.11 and Fig. 8.12 illustrate a comparison of the actual damage assessment with that of the GA based Fuzzy BP and the conventional model respectively.

8.5 Summary

In this chapter, a GA based Fuzzy BP model has been discussed. Conventional Fuzzy BP network makes use of a weight updating rule based on a gradient descent technique to determine its weights. But GAs have turned out to be robust search and optimization techniques outperforming gradient based techniques.

Such a GA based Fuzzy BP network determines its weights with the help of a GA following a real coded system and a Matrix Cross Over Operator mechanism. The performance of the conventional Fuzzy BP and GA based Fuzzy BP networks has been compared over two problems, viz., determination of allowable stress of beams subjected to lateral loads and earthquake damage evaluation.
Table 8.1

Fuzzy linguistic values associated with $\frac{D}{T}$ ratio

<table>
<thead>
<tr>
<th>Grade</th>
<th>Grade expressed as vague concepts</th>
<th>$\frac{D}{T}$ ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Very thick</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>Thick</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>Moderate</td>
<td>3</td>
</tr>
<tr>
<td>4</td>
<td>Thin</td>
<td>4</td>
</tr>
<tr>
<td>5</td>
<td>Very thin</td>
<td>5</td>
</tr>
</tbody>
</table>

Table 8.2

Fuzzy linguistic values associated with Slenderness ratio

<table>
<thead>
<tr>
<th>Grade</th>
<th>Grade expressed as vague concepts</th>
<th>Slenderness ratio (around)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Very short</td>
<td>60</td>
</tr>
<tr>
<td>2</td>
<td>Nearly short</td>
<td>80</td>
</tr>
<tr>
<td>3</td>
<td>Fairly medium</td>
<td>100</td>
</tr>
<tr>
<td>4</td>
<td>Medium</td>
<td>120</td>
</tr>
<tr>
<td>5</td>
<td>Nearly medium</td>
<td>140</td>
</tr>
<tr>
<td>6</td>
<td>Fairly slender</td>
<td>160</td>
</tr>
<tr>
<td>7</td>
<td>Slender</td>
<td>180</td>
</tr>
<tr>
<td>8</td>
<td>Nearly slender</td>
<td>200</td>
</tr>
<tr>
<td>9</td>
<td>Neither slender nor long</td>
<td>220</td>
</tr>
<tr>
<td>10</td>
<td>Just long</td>
<td>240</td>
</tr>
<tr>
<td>11</td>
<td>Fairly long</td>
<td>260</td>
</tr>
<tr>
<td>12</td>
<td>Very long</td>
<td>280</td>
</tr>
</tbody>
</table>
Table 8.3
Permissible (crisp) stress values associated with the fuzzy inputs

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>234</td>
<td>216</td>
<td>199</td>
<td>184</td>
<td>171</td>
<td>159</td>
<td>149</td>
<td>144</td>
<td>131</td>
<td>123</td>
<td>117</td>
<td>111</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>228</td>
<td>206</td>
<td>185</td>
<td>167</td>
<td>152</td>
<td>139</td>
<td>127</td>
<td>122</td>
<td>110</td>
<td>102</td>
<td>96</td>
<td>90</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>225</td>
<td>199</td>
<td>175</td>
<td>154</td>
<td>138</td>
<td>124</td>
<td>112</td>
<td>108</td>
<td>95</td>
<td>88</td>
<td>82</td>
<td>77</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>220</td>
<td>189</td>
<td>160</td>
<td>136</td>
<td>117</td>
<td>102</td>
<td>90</td>
<td>85</td>
<td>73</td>
<td>67</td>
<td>61</td>
<td>57</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>218</td>
<td>185</td>
<td>153</td>
<td>127</td>
<td>92</td>
<td>79</td>
<td>74</td>
<td>62</td>
<td>56</td>
<td>51</td>
<td>47</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\[ A = \frac{SR}{D/T} \quad \text{SR: Slenderness ratio} \quad D/T: \frac{D}{T} \quad \text{Ratio} \]

Table 8.4
Fuzzy linguistic values associated with the inputs to earthquake damage evaluation

<table>
<thead>
<tr>
<th>Earthquake magnitude</th>
<th>Grade expressed as vague concepts</th>
<th>Value</th>
<th>Epicentral distance</th>
<th>Grade expressed as vague concepts</th>
<th>Value (around)</th>
<th>Peak ground Acceleration / Spectral intensity</th>
<th>Grade expressed as vague concepts</th>
<th>Value (around)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Very low</td>
<td>5</td>
<td>1</td>
<td>Very close</td>
<td>3.6</td>
<td>1</td>
<td>Very low</td>
<td>5.29</td>
</tr>
<tr>
<td>2</td>
<td>Low</td>
<td>5.5</td>
<td>2</td>
<td>Little close</td>
<td>5</td>
<td>2</td>
<td>Low</td>
<td>5.58</td>
</tr>
<tr>
<td>3</td>
<td>Nearly medium</td>
<td>6.7</td>
<td>3</td>
<td>Close</td>
<td>6.2</td>
<td>3</td>
<td>Nearly low</td>
<td>6.0</td>
</tr>
<tr>
<td>4</td>
<td>Medium</td>
<td>7.1</td>
<td>4</td>
<td>Very near</td>
<td>11</td>
<td>4</td>
<td>Medium</td>
<td>6.39</td>
</tr>
<tr>
<td>5</td>
<td>Nearly high</td>
<td>7.4</td>
<td>5</td>
<td>Fairly near</td>
<td>55</td>
<td>5</td>
<td>Nearly high</td>
<td>10.46</td>
</tr>
<tr>
<td>6</td>
<td>High</td>
<td>7.7</td>
<td>6</td>
<td>Near</td>
<td>107</td>
<td>6</td>
<td>High</td>
<td>21.20</td>
</tr>
<tr>
<td>7</td>
<td>Very high</td>
<td>7.9</td>
<td>7</td>
<td>Far</td>
<td>130</td>
<td>7</td>
<td>Very high</td>
<td>32.79</td>
</tr>
</tbody>
</table>
Table 8.5
Fuzzy inputs and corresponding damage evaluation for the 9 Japanese earthquakes

<table>
<thead>
<tr>
<th>Earthquake</th>
<th>M</th>
<th>Δ</th>
<th>$A_{MAX}/SI$</th>
<th>D Expected</th>
<th>D Obtained</th>
</tr>
</thead>
<tbody>
<tr>
<td>Matsuhiro '60</td>
<td>5.0</td>
<td>3.6</td>
<td>32.71</td>
<td>0.04</td>
<td>0</td>
</tr>
<tr>
<td>Tokiachi-oki '68</td>
<td>7.9</td>
<td>176</td>
<td>5.96</td>
<td>0.23</td>
<td>0.29</td>
</tr>
<tr>
<td>Miyagi-Ken-Oki '78</td>
<td>7.4</td>
<td>130</td>
<td>5.29</td>
<td>0.59</td>
<td>0.36</td>
</tr>
<tr>
<td>Nihonkai-Chubu '83</td>
<td>7.7</td>
<td>107</td>
<td>6.03</td>
<td>0.18</td>
<td>0.29</td>
</tr>
<tr>
<td>Chiba-Ken-toho-Oki '87</td>
<td>6.7</td>
<td>55</td>
<td>21.2</td>
<td>0.1</td>
<td>0</td>
</tr>
<tr>
<td>Izu-Hanto-toho-Oki '89</td>
<td>5.5</td>
<td>6.2</td>
<td>5.58</td>
<td>0.4</td>
<td>0.4</td>
</tr>
<tr>
<td>Loma Pricta '89</td>
<td>7.1</td>
<td>5</td>
<td>10.46</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Loma Pricta '89</td>
<td>7.1</td>
<td>11</td>
<td>6.39</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>Loma Pricta '89</td>
<td>7.1</td>
<td>54</td>
<td>10.7</td>
<td>0.18</td>
<td>0.16</td>
</tr>
</tbody>
</table>

M Earthquake magnitude  
Δ Epicentral distance  
$A_{MAX}$ Peak ground acceleration  
SI Spectrum Intensity  
D Damage Membership
Fig. 8.1: Structure of a Fuzzy Neuron

Fig. 8.2: Architecture of Fuzzy BP
Fig. 8.3: Fuzzy representation of D/T ratio

Fig. 8.4: Fuzzy representation of Slenderness ratio
Fig. 8.5: Performance Comparison for Trained instances
(Actual Vs GA based Fuzzy BP)
Fig. 8.6: Performance Comparison for Trained instances
(Actual Vs Conventional Fuzzy BP)
Fig. 8.7: Performance Comparison for Untrained instances (Actual Vs GA based Fuzzy BP)
Fig. 8.8: Performance Comparison for Untrained instances (Actual Vs Conventional Fuzzy BP)
Fig. 8.9: Convergence history curve for the GA based Fuzzy BP Model
Fig. 8.10: Fuzzy representation of inputs to Earthquake damage Evaluation
Fig. 8.11: Performance Comparison
(Actual Vs GA based Fuzzy BP)
Fig. 8.12: Performance Comparison
(Actual Vs Conventional Fuzzy BP)