CHAPTER 4

Rule Base Design of Antecedent Fuzzy Variable for IDMT Relay

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"It was the best of times, it was the worst of times, it was the age of wisdom, it was the age of foolishness, it was the epoch of believe, it was the epoch of incredulity, it was the season of light, it was the season of darkness, it was the spring of hope, it was the winter of despair, we had every thing before us, we were all going direct to heaven, we were all going direct to the other way—in short, the period was so far like the present period, that some of its noisiest authorities insisted on its being received, for good or for evil. In the superlative degree of comparison only."

Charles Dickens
A tale of Two cities, 1859
Chapter 4.

Rule Base Design of Antecedent Fuzzy Variable for IDMT Relay

4.1 Introduction

In the design of a power system, three aspects are generally considered namely normal operation, prevention of electrical failure and the reduction of damaging effects caused by an electrical failure [62]. There should be devices which will disconnect the faulty equipment of the power system with the help of circuit breakers (C.B.) associated with the said equipment, when it suffers from a short circuit or behaves in an abnormal fashion that might cause damage to the equipment or interfere with the effective operation of the rest of the power system [62,77].

Fig.4.1 shows the location of a conventional relay and the sequence of events leading to the final disconnection of faulty equipment [77]. These events are:

(i) Detection of primary condition.
(ii) Processing of the detected information.
(iii) Resulting chain of commands to C.B.

The power system elements generally consist of generators, transformers, transmission lines, cables, synchronous and induction motors and switch gears. Each of them develop some faults sooner or later.

![Fig. 4.1 Conventional Relay location in power system](image-url)
Extensive work had been done in this field and also in the application of on-line digital and analogous computers to power system protection with the development of low cost micro computer system/micro processor, the economics are changing at a fast rate and investigators are trying to develop dedicated digital protection schemes which closely imitate the existing relaying practices [50]. Each relaying function is served by a separate unit which requires a highly parallel distributed processor network, in which each processor is strictly dedicated to a particular protective function.

With the advent of fuzzy systems and Neural Network an expert system or adaptive system may be developed to act as a digital relay [72]. The concept of fuzzy sensor as a relay may be used to develop the above system. The inverse definite time relay characteristics or data may be fuzzified and after a required fuzzy mathematical manipulation or rule based reasoning the result may be defuzzified to obtain the prescribed characteristic of relay performance [106]. The antecedent or input variable (one or two input variables) may be fuzzified from its crisp or singleton value and an NN is trained to design the membership function of input or antecedent variables [85-88].

4.2 Characteristics of IDMT relay

Single input protection schemes are actuated by a single input taken from the power systems in abnormal (Faulty) condition [62]. The schemes work basically either on presence or on absence of selected input quantity. These relays operate only on the basis of the system current exceeding a normal value.

Inverse time over current relay type CDG11 manufactured by GEC Alsthom is preferred for fuzzifying its rating [56]. These relays are available in the standard current setting ranges of 50-200%, 20-80% and 10-40% of 1A or 5A. The 5A rating is considered here. The technical data are:

- **Current Rating** = 1A or 5A
- **IDMT Setting** = 50-200% in seven equal steps of 25%
  - 20-80% in seven equal steps of 10%
  - 10-40% in seven equal steps of 5%
- **Operating Time** = 0-3 seconds or at 10 times 0-1.3 seconds

The relay characteristics are adjusted to have a definite minimum time of operation for plug setting multiplier higher than 20 in general. Thus the actual relay characteristic becomes an inverse characteristic below this value of Plug Setting Multiplier (PSM) and a straight line above this value.
The plug setting steps are calibrated in terms of time setting multiplier (TSM) which is defined as:

\[
TSM = \frac{Actual\text{- operating}\text{- time}\text{- of}\text{- relay}}{Calibrated\text{- operating}\text{- time}\text{- for}\text{- a}\text{- particular}\text{- }PSM}
\]

Fig. 4.2 shows a standard IDMT characteristics curve drawn in logarithmic scale between PSM and operating time. The original curve of IDMT relay i.e. CDG11 obtained from the manual of GEC Alsthom, India is attached in “appendix A” of this thesis. For standard IDMT relays, the recommended expression for time current relationship is given by:

\[
T = \frac{0.14}{I^{0.02} - 1}
\]

Here \( T \) = Operating time of relay and \( I \) = Operating current of relay.

The static time over current relays generally require an auxiliary current transformer (C.T.) to reduce the main C.T. secondary current still further by 10 times. Static over current relay essentially consists of a rectifying circuit, an integrating circuit and two level detector arrangements (see Fig. 4.3). Fig. 4.4 shows the proposed fuzzy sensor scheme for IDMT over current relay [93]. These relays operate after a fixed interval of time, after the fault current \((I_f)\) exceeds the pick up current \((I_p)\) level. The working behavior of IDMT relay would be governed by the characteristics curve shown in Fig. 4.5.
4.3 Membership Function

Characteristic curve of IDMT relay is shown in Fig. 4.5, original curve of GEC Alsothm India is attached in Appendix A. This IDMT relay is fuzzified as shown in Fig. 4.5 with three membership function small, medium, high for plug setting multiplier (PSM) and its corresponding operating time.

Fig. 4.5 Characteristics curve of IDMT relay after fault has developed.
4.3.1 Data Driven Fuzzy Variable Design

Here membership functions development by examining data and by extracting the decision boundaries have been carried out [109]. Data driven design in this context assumes that the decision boundaries are known or they are easily extractable from the data set. This means it is known that which point in the input or antecedent product space belongs to which output class [102].

The decision boundary concept is an essential element of design for both fuzzy variable development and for rule formation. Fuzzy variable design and rule formation are closely related.

There are two types of data: crisp and fuzzy. Crisp data have possibility of 1.0 to represent reality. Fuzzy data can come from a physical measurement system but must be assigned membership function by human interpretation or by some mathematical criterion [52]. Partitioning is an attempt to find a decision boundary between two data points on a product space. A known decision boundary means that all input-output classes are known. In this research work, data have been driven from its characteristic curve of relay shown in Fig. 4.5.

4.3.2 Point Membership Function

In the presence of a single crisp point but no other information, fuzziness around the crisp point may be defined by a pyramid, which produces triangular projections on the both product spaces [109]. Input plug setting current or antecedent variables \( I_{pl} \) will form a \( I_{pl} \times \mu \) space which would define the membership function of antecedent variable when there are 'N' crisp points describing the relationship of interest, point membership function development can be repeated for each point on the product space [85-88]. This phenomena may be illustrated using corresponding base area pyramids, the membership functions produced by projection of mapping of crisp points \( N_1, N_2, N_3 \) of Fig. 4.5 yield an intersection as shown in Fig. 4.6 by bird's eye view.

Looking into the birds-eye-view of pyramidal shape of membership function from input or antecedent side perpendicular to the plane of elevation, the triangular planes of pyramid will show the shape of its membership function for antecedent variables, the \( I_{pl} \times \mu \) plane of Fig. 4.6 is shown in Fig. 4.8 which is the membership function of antecedent variables in bell shapes for small, medium and high level of fault currents [71]. For the predicates small, medium and high one have to obtain the membership functions. In general 'N' crisp points on input product space require 'N' mapping rules with 'N' pairs of point membership functions. When all outputs classes are distinct, the exhaustive solution becomes the only solution which is referred to as Fuzzy Associative Memories (FAM) rules.
Fig 4.6 Birds –eye-view of Membership Function for antecedent variable

Fig. 4.7 depicts the design interface of antecedent variables for IDMT relay. This interface is used to design the input/output fuzzy variable and fuzzy inference system for rule based sensor. This FIS received plug setting current as input and produces operating time as an output.

Fig. 4.8 illustrates the membership function of antecedent variable (i.e. plug setting current) [94] preferring bell shaped curve, which is most widely used membership curve for input variable. The choice of shape of membership function depends on the reasoning skill of an expert person.

Fig 4.7 Fuzzy inference engine designed for IDMT relay
The designed membership function of consequent variable [94] are shown in Fig. 4.9 for its low, medium and high linguistic variable in given universe of discourse. This membership is obtained according to the membership curve of antecedent variable of IDMT relay shown in Fig. 4.5.

Fig. 4.8 Membership function in bell shape of antecedent variables

Fig. 4.9 Membership function in triangular shape of consequent variables

4.4 Rule Base Design

According to the characteristics curve of IDMT relay FAM rules can be summarized in the following table [25].
The above FAM rules can be written in form of IF –THEN as given below.

\[ \text{If } I_p \cdot P_s \quad \rightarrow \quad O_t \cdot P_h \]
\[ \text{If } I_p \cdot P_m \quad \rightarrow \quad O_t \cdot P_m \]
\[ \text{If } I_p \cdot P_h \quad \rightarrow \quad O_t \cdot P_l \]  

...(4.1)

These rules are referred to as fuzzy associative memories (FAM) rules. The rule base design interface obtained from the MATLAB software is shown in Fig. 4.10 for three FAM rules.

**Table 4.1 Fuzzy Associative Memories (FAM) rule Table**

<table>
<thead>
<tr>
<th></th>
<th>H</th>
<th>M</th>
<th>L</th>
</tr>
</thead>
<tbody>
<tr>
<td>I_p</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S</td>
<td></td>
<td>R_1</td>
<td></td>
</tr>
<tr>
<td>M</td>
<td></td>
<td></td>
<td>R_2</td>
</tr>
<tr>
<td>H</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The above FAM rules can be written in form of IF –THEN as given below.

\[ \text{If } I_p \cdot P_s \quad \rightarrow \quad O_t \cdot P_h \]
\[ \text{If } I_p \cdot P_m \quad \rightarrow \quad O_t \cdot P_m \]
\[ \text{If } I_p \cdot P_h \quad \rightarrow \quad O_t \cdot P_l \]  

...(4.1)

These rules are referred to as fuzzy associative memories (FAM) rules. The rule base design interface obtained from the MATLAB software is shown in Fig. 4.10 for three FAM rules.

**Fig. 4.10 Rule base design for inference engine**

**FAM Rule1** : IF plug setting current level is Small THEN operating time for relay is High.

**FAM Rule2** : IF plug setting current is Medium THEN operating time for relay is Medium.

**FAM Rule3** : IF plug setting current is High THEN operating time of relay is Low.

In equation 4.1  

\[ I_p = \text{Plug setting current level.} \]

\[ O_t = \text{Operating time of relay} \]

\[ P_s = \text{Predicate Small} \]

\[ P_m = \text{Predicate Medium} \]

\[ P_h = \text{Predicate High} \]
In the context of fuzzy system design, uncertainties are represented by membership functions and by their individual properties. The above discussions mainly included the determination of the number and location of membership functions. One can also examine their shape without being concerned about their number and location on the universe of discourse.

The geometrical shape of membership function is the characterization of uncertainty in the corresponding fuzzy variable. Nevertheless, the shape of a membership function cannot be formed arbitrarily because arbitrary design can produce unpredictable results in the basic fuzzy inference algorithm. The triangle and trapezoid are the two geometric shapes commonly used to represent uncertainties [52]. The height of a membership function determines the maximum value of membership function. In Fig.4.5 the height of membership functions are equal with equal amount of fuzziness (i.e. 100%). From the basic definition of membership function, the width of occupancy is the measure of fuzziness. In Fig.4.5 membership function $N_1$ is most fuzzy than rest of the two $N_2$ & $N_3$, again $N_3$ has least fuzziness [106,109].

From the inverse characteristics of relay (Fig.4.5) one can see that for low fault current level the operating time of relay would be high and vice-versa.

A fuzzy set defines a point in a fuzzy universe of discourse. A fuzzy system defines a mapping between two fuzzy universe of discourses. A fuzzy system 'S' maps fuzzy sets to fuzzy sets. Thus a fuzzy system 'S' is a transformation $S: I_p^n \rightarrow O_p^o$. The $n$-dimensional units hypercube $I_{p^n}$ contains all the fuzzy subsets of the input universe of discourse [106].

$$I_{p^n} = (I_{p1}, I_{p2}, I_{p3}, \ldots \ldots \ldots \ldots I_{pn}) \ldots (4.2)$$

$O_i^o$ contains all the fuzzy subsets of the output universe of discourse.

$$O_{p}^o = (O_{1}, O_{2}, O_{3}, \ldots \ldots \ldots O_{m}) \ldots (4.3)$$

They map close inputs to close outputs, which are referred as fuzzy associative memories or FAMs. The FAM rule [109].

$\text{IF } 'I_{pl}^S' \text{ is } 'P_S' \text{ THEN } O_{t}^S \text{ IS } P_H$ .... (4.4)

May be encoded by $(P_S, P_H)$

In general a FAM system $F: I_{p}^n \rightarrow O_{t}^o$ encodes and processes in parallel a FAM bank of FAM rules.

$(P_{S1}, P_{H1}), (P_{S2}, P_{H2}), (P_{S3}, P_{H3}), \ldots \ldots \ldots (P_{SM}, P_{HM}) \ldots (4.5)$

Fuzzy systems estimate functions with fuzzy set samples $(P_{Si}, P_{Hi})$, neural samples use numerical-point samples. Engineers sometimes call the fuzzy set association $(P_{Si}, P_{Hi})$ a "rule". Here
\( P_n \) is referred as antecedent term and \( P_{hi} \) is referred as consequent term. The antecedent variables with referred to membership function (Fig.4.5) would be -

\[
(I^{S}_{pl1}, I^{S}_{pl2}, I^{S}_{pl3}, I^{S}_{pl4}, I^{M}_{pl1}, I^{M}_{pl2}, I^{M}_{pl3}, I^{M}_{pl4}, I^{H}_{pl1}, I^{H}_{pl2}, I^{H}_{pl3}, I^{H}_{pl4})
\]  

...(4.6)

The respective consequent variable would be -

\[
(O^{H}_{11}, O^{H}_{12}, O^{H}_{13}, O^{H}_{14}, O^{M}_{11}, O^{M}_{12}, O^{M}_{13}, O^{M}_{14}, O^{L}_{11}, O^{L}_{12}, O^{L}_{13}, O^{L}_{14})
\]  

...(4.7)

### 4.5 Rule Base Inference

Three rules obtained from FAM rule table can be viewed from the rule viewer for different plug setting current as shown in Fig. 4.11 (a), (b). Fig. 4.11 (a) shows the rule firing process for \( Ip_l = 7 \) Amp, for this plug setting current only the second rule is firing and giving fuzzy data as shown in this figure at the right side. In the same manner Fig. 4.11(b) shows rule firing process for \( Ip_l = 10 \) Amp.

Simulated characteristics curve of IDMT relay, input as plug setting current and output as operating time is shown in Fig. 4.12. This curve is not smooth as compare to the curve in Fig. 4.5, this is due to less number of rules (only 3 rules). By increasing the number of rules this problem may be overcome, but initially only 3 rules has been considered to check the performance of IDMT relay as fuzzy relay or fuzzy sensor. From the curve shown in Fig.4.12 it is clear that, the simulated version of characteristics curve of IDMT relay also satisfied the rules of original curve. In this curve it is clear that if will increase plug setting current then operating time will decrease. Hence it’s nature is analogous to the original IDMT curve.

![Fig. 4.11 (a) Rule base inference process for \( Ip_l = 7 \) Amp](image_url)
The fuzzified antecedent multiplier of plug setting current level $I_{pl}$ (Equation 4.14) are input to the neural network.

Antecedent variables for IDMT relay have been designed using fuzzy logic technique and the same variables are being used for NN training [79]. The results must comply the performance of IDMT relay. The weight of input to hidden layer ($i^{th}$ layer to $j^{th}$ layer) would provide us the trained values of antecedent variables. This is the objective of this research. The membership functions for antecedent variables of IDMT relay trains an ANN for several iteration.
4.6.1 Network Design for IDMT Relay

It is considered that some knowledge is incorporated in fuzzy system. This basic knowledge does not allow the fuzzy system to fit well enough the application in hand, and a tuning of fuzzy system has to be done [109]. One of the several methods to perform this tuning is an external tuning method using a ‘correcting’ neural network [14]. This hybrid configuration (architecture) [64] is shown in Fig. 4.13.

The present work of NN training comprises the concept of transforming data via an artificial neural network (ANN) model from fuzzy system to output domain by tuning the NN [14]. The ANN proposed is constructed with one input layer having two neurons, one hidden layer with six neurons and an output layer with two neurons (2-6-2) (see Fig. 4.14). For each neuron \( j \) in the hidden layer and neuron \( k \) in the output layer, the net inputs are given by:

\[
I_{ji} = \sum_{i=1}^{N_j} W_{ji} O_i \quad j = 1,2, \ldots \ldots, N_j \quad \text{...(4.8)}
\]

and

\[
I_{jk} = \sum_{j=1}^{N_j} W_{kj} O_j \quad k = 1,2, \ldots \ldots, N_k \quad \text{...(4.9)}
\]

respectively. The neuron output is given by

\[
O_i = I_{pli} \quad \text{(input signals)} \quad \text{...(4.10)}
\]

\[
O_j = \frac{1}{1 + e^{-I_{plj}}} \quad \text{...(4.11)}
\]

\[
O_k = \frac{1}{1 + e^{-I_{plk}}}
\]
The connection weights $W_{ji}$ and $W_{kj}$ are updated after each iteration. They are changed after $\cdot N$ input/output pair patterns have been presented [64]. Then for a presentation $P$, the sum of squared errors to be minimized is given by:

$$E_P = \sum_{N=1}^{N'} \sum_{k=1}^{N_j} (t_{p_k} - O_{p_k})^2$$  \hspace{1cm} (4.12)

Here $t_{p_k}$ = target output and $O_{p_k}$ = computed output value at output node $k$ for the $N^{th}$ input/output pair in ‘P’ presentation.

### 4.6.2 Neural Network Training

The characteristic curve of IDMT relay has been fuzzified using pyramidical Bird’s eye view and its front views have been projected in X-axis (see Fig.4.6) to get triangular shape membership function from the triangular front face of pyramids (see Fig.4.6) characteristic curve at $N_1$, $N_2$ and $N_3$. Points has been assigned linguistic values small, medium and high respectively. After designing the fuzzy universe of discourse for antecedent and consequent variables as described above the training data sets are obtained from X-axis and Y-axis of Fig. 4.6 respectively. The training data set thus obtained is used to train a neural network shown in Fig.4.14 to optimize the output data. The optimized data are used to develop FAM rules for inference engine. The design of antecedent variables and training of neural network have been carried. A comparison of desired and simulated membership function for antecedent variables have been found and tabulated in Table 4.4, as a result.

Twelve data with their membership functions have been identified from Fig. 4.6 and equation 4.6 and 4.7 to train the neural network.

The antecedent variables are taken from original curve of IDMT relay (See Appendix A) and can be numerically written referring equation 4.6 and Fig.4.6 as below -

( 2.5, 3, 4, 5, 6, 7, 8, 9, 10, 15, 17.5, 20 ) \hspace{1cm} (4.13)

these data are treated as training data set and their membership are obtained from Fig. 4.8 as below-

(1, 1, 0.96, 0.44, 0.28, 0.91, 1, 0.96, 0.001, 1, 1, 1) \hspace{1cm} (4.14)

The corresponding consequent variables obtained after mapping plug setting current with operating time from Fig. 4.5 and Fig. 4.6 as given below -

(0.78, 0.65, 0.58, 0.52, 0.48, 0.46, 0.44, 0.41, 0.40, 0.35, 0.33, 0.32) \hspace{1cm} (4.15)
and may be treated as training data set, their memberships are obtained from Fig. 4.9 as below -

\[(0.6, 0.75, 0.4, 0.1, 0.76, 0.92, 0.90, 0.60, 0.0, 1, 0.6, 0.4) \ldots (4.16)\]

\[
\begin{align*}
\text{small} & \rightarrow | & \text{Medium} & \rightarrow | & \text{High} & \rightarrow |
\end{align*}
\]

Table 4.2 Training data set and its membership function for NN training

<table>
<thead>
<tr>
<th>Data Point</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>Ip</td>
<td>2.5</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>9</td>
<td>10</td>
<td>15</td>
<td>17.5</td>
<td>20</td>
</tr>
<tr>
<td>(\mu_{\text{Ip}})</td>
<td>1</td>
<td>1</td>
<td>0.96</td>
<td>0.44</td>
<td>0.28</td>
<td>0.91</td>
<td>1</td>
<td>0.96</td>
<td>0.001</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Ot</td>
<td>0.78</td>
<td>0.65</td>
<td>0.58</td>
<td>0.52</td>
<td>0.48</td>
<td>0.46</td>
<td>0.44</td>
<td>0.41</td>
<td>0.40</td>
<td>0.35</td>
<td>0.33</td>
<td>0.32</td>
</tr>
<tr>
<td>(\mu_{\text{Ot}})</td>
<td>0.6</td>
<td>0.75</td>
<td>0.4</td>
<td>0.1</td>
<td>0.76</td>
<td>0.92</td>
<td>0.90</td>
<td>0.60</td>
<td>0.00</td>
<td>1</td>
<td>0.6</td>
<td>0.4</td>
</tr>
</tbody>
</table>

Fuzzy membership function may be created for fuzzy classes of an input data set (Takagi and Hayashi, 1991) [72]. We select a number of input data values as training data set. The training data set is used to train the neural network. An input training data set and its membership function is considered for NN training shown in Fig. 4.14 and tabulated in Table 4.2.

Fig. 4.14 NN for realization of IDMT Relay antecedent variable
Weights for input to hidden and hidden to output layers are obtained from equation 4.14 and 4.16 after modification as shown in Table 4.3.

Table 4.3 The initial assigned weights to the paths connecting inter layer nodes

<table>
<thead>
<tr>
<th>Input to hidden inter layer weights</th>
<th>Assigned values to input to hidden layer elements</th>
<th>Hidden to output layer weights</th>
<th>Assigned values to hidden to output layer elements</th>
</tr>
</thead>
<tbody>
<tr>
<td>( W_1 )</td>
<td>0.35</td>
<td>( W_1^2 )</td>
<td>0.45</td>
</tr>
<tr>
<td>( W_2 )</td>
<td>0.75</td>
<td>( W_2^2 )</td>
<td>0.9</td>
</tr>
<tr>
<td>( W_3 )</td>
<td>0.25</td>
<td>( W_3^2 )</td>
<td>0.45</td>
</tr>
<tr>
<td>( W_4 )</td>
<td>0.01</td>
<td>( W_4^2 )</td>
<td>0.01</td>
</tr>
<tr>
<td>( W_5 )</td>
<td>0.45</td>
<td>( W_5^2 )</td>
<td>0.35</td>
</tr>
<tr>
<td>( W_6 )</td>
<td>0.75</td>
<td>( W_6^2 )</td>
<td>0.35</td>
</tr>
<tr>
<td>( W_7 )</td>
<td>0.75</td>
<td>( W_7^2 )</td>
<td>0.85</td>
</tr>
<tr>
<td>( W_8 )</td>
<td>0.45</td>
<td>( W_8^2 )</td>
<td>0.80</td>
</tr>
<tr>
<td>( W_9 )</td>
<td>0.01</td>
<td>( W_9^2 )</td>
<td>0.01</td>
</tr>
<tr>
<td>( W_{10} )</td>
<td>0.95</td>
<td>( W_{10}^2 )</td>
<td>0.01</td>
</tr>
<tr>
<td>( W_{11} )</td>
<td>0.01</td>
<td>( W_{11}^2 )</td>
<td>0.35</td>
</tr>
<tr>
<td>( W_{12} )</td>
<td>0.45</td>
<td>( W_{12}^2 )</td>
<td>0.01</td>
</tr>
</tbody>
</table>

The FAM rules may be developed in Neuro-linguistic form [109] (see Table 4.2)

**FAM Rule 1**: IF plug setting current level is 2.5 Amp with 1 fuzzy membership function (Fuzzy grade of truth) THEN Relay Operating time is 0.78 second with 0.6 membership function (fuzzy function grade of truth)

**FAM Rule 2**: IF plug setting current level is 7Amp with 0.91 membership function THEN Relay operating time is 0.46 second with 0.92 membership function

**FAM Rule 3**: IF plug setting current level is 15 Amp with 1.0 membership function THEN relay operating time is 0.35 second with 1.0 membership function.

### 4.7 Simulation Results

ANN shown in Fig. 4.14 is trained after assigning initial weights from Table 4.3 and using training data given in Table 4.2, obtained results are tabulated in Table 4.4 and Table 4.5, containing input and output data set for its desired and simulated values. The error thus obtained is in
acceptable range. It is tried to illustrate a conceptual design of the antecedent variables for the IDMT relay to develop it as a fuzzy sensor for power system protection. The training performance curve of neural network is shown in Fig.4.14. The training goal was met after 100 epochs.

![Graph showing training performance curve](image)

**Fig. 4.14 Performance of neural network shown in Fig.4.13**

### 4.8 Discussion

The characteristic curve of IDMT relay has been fuzzified to design the antecedent variables of IDMT relay as fuzzy sensor. This curve has also fuzzified referring the theories like bird’s-eye-view and point membership function of input/output data sets.

The fuzzified antecedent variables obtained from Fig. 4.5 is used to train the neural network. The twelve data, four from each linguistic values i.e. small, medium and high respectively along with their corresponding membership functions are considered for training the Neural Network. The desired values of antecedent variables are obtained from the characteristic curve and it is compared with the simulated results. One can see that errors thus obtained (see Table 4.4 and 4.5) are small and are in acceptable range. Thus a perfectly trained Neuro-Fuzzy systems provides a tool or blue print to develop hardware and software of fuzzy relay sensor.
### Table 4.4 Comparison of desired and simulated membership functions of antecedent variables

<table>
<thead>
<tr>
<th>S.No.</th>
<th>Antecedent Variables 'Ipl' Amperes</th>
<th>Desired antecedent membership functions</th>
<th>Simulated antecedent membership function</th>
<th>Error</th>
</tr>
</thead>
<tbody>
<tr>
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### Table 4.5 Comparison of desired and simulated membership functions of consequent variables

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