CHAPTER 7

NEURO-FUZZY LOGIC BASED SMES CONTROL

In this chapter, transient stability investigation of a single machine connected to
infinite bus is carried out using Neuro-Fuzzy logic based SMES. The complete model
of SMES using Neuro-Fuzzy logic controller for simulation is presented. Two Neuro-
Fuzzy controllers are designed to obtain the estimated active power and reactive
power. From P-SMES controller with which the system shows optimal dynamic
performance at the representative operating condition is used as a training data for the
Neuro-Fuzzy logic controller. In this chapter basic principles of Neuro-Fuzzy
controller are discussed in brief. The results of investigation are presented for SMIB
for critical fault clearing time, for time higher than critical fault clearing time and for
different loading conditions. The comparative study of P-SMES and fuzzy logic
based SMES for SMIB is investigated. For multimachine system, the results of
investigation for critical fault clearing time in the presence of SMES is also given.

7.1 Neuro – Fuzzy Controller

An adaptive network, as the name suggest, is a network structure consisting of
nodes and directional links through which nodes are connected. Moreover part or all
of the nodes are adaptive, which means their output depend on the parameters
pertaining to these nodes, and learning rule specifies how these parameters should be
changed to minimize a prescribed error measure.

7.1.1 Architecture and basic Learning Rule [77,120]

An adaptive network, shown in Fig. 7.1, is a multi-layer feed-forward network in
which each node performs a particular function (node function) on the incoming
signal as well as set of parameter pertaining to this node. The formula for the node
function may vary from node to node, and the choice of each node functions depends
on the overall input-output function which the adaptive network only indicate the
flow direction of signals between nodes; no weights are associate with links.
Fig. 7.1 Architecture of Adaptive Network
To reflect different adaptive capabilities, we use both circle and square nodes in an adaptive network. A square (adaptive node) has parameters while a circle node (fixed node) has none. The parameter set of an adaptive network is the union of the parameter sets of each adaptive node. In order to achieve a desired input-output mapping, these parameters are updated to given training data and a gradient-based learning procedure described below.

Suppose that a given adaptive network has L layers and the kth layer has n nodes. We can denote a node in the ith position of the kth layer by \((k, i)\), and its node function (or node output) by \(O_k^i\). Since a node output depends on its incoming signals and its parameters set, we have

\[
O_k^i = O_k^i(O_{k-1}^{i-1}, \ldots, O_{a,b,c}^j, \ldots)
\]  
(7.1)

Where \(a, b,\) and \(c\) are the parameters pertaining on this node.

Assuming the given training data set has \(P\) entries, we can define the error measure (or energy function) for the \(p\)th (\(1 \leq p \leq P\)) entry of training as the sum of square errors:

\[
E_p = \sum_{m=1}^{L} (T_{m,p} - O_{m,p})^2
\]  
(7.2)

Where \(T_{m,p}\) is the \(m\)th component of the \(p\)th output vector, and \(O_{m,p}\) is the \(m\)th component of actual out vector produced by the presentation of the \(p\)th input vector. Hence the overall error measure is

\[
E = \sum_{p=1}^{P} E_p
\]  
(7.3)

In order to develop a learning procedure that implements gradient descent in the parameter space, first we have to calculate the error rate \(\delta E_p / \delta O\) for the \(p\)th training data and for each node output \(O\). the error rate for the output node at \((L, i)\) can be calculated from the mentioned relation:

\[
\frac{\delta E_p}{\delta O_{i,p}^L} = -2(T_{i,p} - O_{i,p}^L)
\]  
(7.4)
for the internal node at \((k, i)\), the error rate can be derived by the chain rule:

\[
\frac{\delta E_p}{\delta O_{i,p}} = \sum_{m=1}^{k+1} \frac{\delta E_p}{\delta O_{m,p}} \frac{\delta O_{m,p}}{\delta O_{i,p}}
\]  

(7.5)

Where \(1 \leq k \leq L-1\), that is, the error rate of an internal node can be expressed as a linear combination of the error rates of the nodes in the next layer, therefore, for all \(1 \leq k \leq L\) and \(1 \leq i < (k)\), we can find \(\frac{\delta E_p}{\delta O_{i,p}}\) by above two relations.

Now if \(\alpha\) is a parameter of given adaptive network, we have

\[
\frac{\delta E}{\delta \alpha} = \sum_{\alpha' \in S} \frac{\delta E_p}{\delta \alpha'} \frac{\delta \alpha'}{\delta \alpha}
\]  

(7.6)

where, \(S\) is the set of nodes whose outputs depend on \(\alpha\). Then the derivative of the overall error measure \(E\) with respect to \(\alpha\) is

\[
\frac{\delta E}{\delta \alpha} = \sum_{p=1}^{n} \frac{\delta E_p}{\delta \alpha}
\]  

(7.7)

Accordingly, the update formula for the generic parameter \(\alpha\) is

\[
\Delta \alpha = -\eta \left(\frac{\delta E_p}{\delta \alpha}\right)
\]  

(7.8)

In which \(\eta\) is a learning rate can be further expressed as

\[
\eta = \left(\sum_{\alpha} \left(\frac{\delta E}{\delta \alpha}\right)^2\right)^{1/2}
\]  

(7.9)

where, \(k\) is the step size, the length of each gradient transition in the parameter space. Usually, we can change the value of \(k\) to vary the speed of convergence.

7.1.2 Hybrid Learning Rule

Though we can apply the gradient method to identify the parameters in an adaptive network, the method is generally slow and is likely to become trapped in local minimum. Here we propose a hybrid learning rule that combines the gradient
method and the least squares estimate (LSE) to identify parameters. Taking one output of the adaptive network

\[ \text{Output} = F(I, S) \quad (7.10) \]

Where \( I \) is the set of input variables and \( S \) is the set of parameters. If there exist a function \( H \) such that the composite function \( H \circ F \) is linear in some of the elements of \( S \), then these elements can be identified by least square method, or we can say, if the parameter set \( S \) can be decomposed into two sets

\[ S = S_1 \oplus S_2 \quad (7.11) \]

(Where \( \oplus \) represents direct sum) such that \( H \circ F \) is linear in the elements of \( S_2 \), then we can say

\[ H(\text{output}) = H \circ F(I, S) \quad (7.12) \]

Which is linear in the elements of \( S_2 \). Now given values of elements of \( S_1 \), we can plug \( P \) training data into above expression and obtain a matrix equation:

\[ AX = B \quad (7.13) \]

Where \( X \) is an unknown vector whose elements are parameters in \( S_2 \). Let \( |S_2| \) has a dimension of \( M \) then the dimension of \( A \), \( X \) and \( B \) are \( P \times M \), \( M \times 1 \) and \( P \times 1 \), respectively. Generally \( P > M \), so this is an over determined problem and generally there is no exact solution. So, a least square estimate (LSE) of \( X \), \( X^* \), is sought to minimize the squared error \( \| AX - B \| \). We can combine the gradient method and square estimates to update the parameters in an adaptive network. Each epoch of this hybrid is composed of a forward pass and a backward pass. In forward pass, we supply input data and functional signals go forward to calculate each node output until the matrices \( A \) and \( B \) are obtained and the parameters in \( S_2 \) are identified by sequential least square formulas. In backward pass, error rates (the derivative of the error with respect to each node output) propagate from the output end towards the output end, and the parameters in \( S_1 \) are updated by the gradient method.
**7.2 ANFIS: Adaptive – Network – Based - Fuzzy Inference System**

ANFIS [77,120] has two inputs x and y and one output. Rule base contains fuzzy if-then rules of Takagi and Sugeno’s type. Architecture of ANFIS is given below:

Fig 7.1 shows equivalent ANFIS architecture. The node functions in the same layer are of the same function family as described below:

**Layer 1:** Every node I in this layer is a square node with node function

\[ O_I = \mu_{A_I}(x) \]  

(7.14)

Where \( x \) is the input to node I, and \( A_I \) is the linguistic label (membership function) associated with this node function. Usually we choose \( \mu_{A_I}(x) \) to be bell-shaped with maximum equal one and minimum equal zero, such as:

\[ \mu_{A_I}(x) = \frac{1}{1 - \left(\frac{(x - c_I)}{a_I}\right)^2} \]  

(7.15)

where \( \{a_I, b_I, c_I\} \) are the parameter set. As the value of these parameters changes, the bell-shaped function varies accordingly, parameters in this layer are referred to as premise parameters. Other type of membership function can also be used.

**Layer 2:** Every node in this layer is labeled \( L \) which multiplies the incoming signals and sends the product out. For instance,

\[ w_I = \mu_{A_I}(x) \times \mu_{B_I}(y) \text{,} \quad i = 1,2,3,\ldots,9 \]  

(7.16)

**Layer 3:** Normalized firing strengths: Every node in this layer is a circle node labeled \( N \). The \( i^{th} \) node calculates the ratio of the \( i^{th} \) rule’s firing strength:

\[ \overline{w}_I = \frac{w_I}{w_1 + w_2} \text{,} \quad i = 1,2,3,\ldots,9 \]  

(7.17)

**Layer 4:** Consequent parameters: Every node I in his layer is a square node with a node function

\[ O_I^4 = \overline{w}_I f_I = \overline{w}_I (p_I x + q_I y + r_I) \]  

(7.18)
Where \( w_t \) is the output of layer 3, and \( \{p, q, r\} \) is the parameter set.

Layer 5: The single node in this layer is a circle node labeled \( \Sigma \) that computes the overall outputs as the summation of all incoming signals, that is,

\[
O_r^5 = \text{overall output} = \frac{\sum_i w_i f_i}{\sum_i w_i}
\]  \hspace{1cm} (7.19)

From the proposed ANFIS architecture, it is observed that given the values of premise parameters, the overall output can be expressed as linear combinations of the consequent parameters. In forward pass of the hybrid learning algorithm functional signals go forward till layer 4 and the consequent parameters are identified by least square estimate. In backward pass, the error rates propagate backward and the premise parameters are updated by gradient descent.

### 7.3 System Investigated for Fuzzy Logic Controlled Application

In order to examine the effectiveness of Neuro-Fuzzy logic based SMES on transient stability of power system, studies were carried out on two systems.

1. Transient stability investigation for SMIB with Neuro-Fuzzy logic based SMES
2. Transient stability investigation for multi-machine system with Neuro-Fuzzy logic based SMES

#### 7.3.1 Transient Stability Investigation for SMIB with Neuro-Fuzzy Logic Based SMES

In order to examine the effectiveness of Neuro-Fuzzy logic based SMES on transient stability of power system; studies were carried out on a sample system considered in Fig. 3.2 given in chapter 3 for illustrating the procedure for evolving Neuro-Fuzzy controller in the presence of SMES.
A Neuro-Fuzzy system describes a fuzzy rule based model using neural network like structure. Two Neuro-Fuzzy controllers are designed to obtain the estimated active power and reactive power. From P-SMES controller with which the system shows optimal dynamic performance at the representative operating condition is used as a training data for the Neuro-Fuzzy logic controller. For transient stability investigations, Neuro-Fuzzy logic based SMES controller is implemented taking into consideration the deviation in rotor angle, $\Delta \delta$, rotor relative angular velocity, $\Delta \omega$ as input variable to Neuro-Fuzzy controller to obtain estimated active power $P_d$. Change in terminal voltage, $\Delta v$ and change in error in voltage, $cev$, as input variables to Neuro-Fuzzy controller to obtain estimated reactive power $Q_d$.

The first layer of neuro-fuzzy architecture describes the membership functions of input variables. With the neural network, five membership functions (triangular) are generated for each input variable. The second layer nodes are connected to only two nodes from the first layer, each one of which describes a condition about an input variable. The nodes in the second layer thus perform the ‘AND’ operator in fuzzy rules. Hence, the number of links connected to a node in the second layer equals the number of input variables. There are nine control rules for each Neuro-Fuzzy controller. The nodes in the third layer give the normalized firing strength of each rule. In the fourth conclusion inferred by fuzzy rule is computed. Then conclusion of all the fuzzy rules is combined in the fifth layer to get output.

A three-phase fault is assumed to be on one of the lines near generator terminals and cleared by opening one of the faulted lines. The swing curves are obtained for the various cases considered in the following paragraphs. The investigations have been carried out for the following two cases:-

1. Transient Stability investigations with fuzzy controlled SMES for different loading conditions.

2. Transient Stability investigations with fuzzy controlled SMES for different fault clearance time for representative operating conditions.
7.3.1.1 Transient Stability Investigation with Neuro-Fuzzy Controlled SMES for Different Loading Conditions

Transient stability investigations have been carried out using Neuro-Fuzzy controlled SMES. To observe the performance of the system considered swing curves is plotted in Figs. 7.2 for the system conditions given in Table 7.1. System gets stabilized for all the conditions considered. For all the conditions fault is cleared at critical clearing time i.e. \( TFC = 0.2 \) seconds.

<table>
<thead>
<tr>
<th>System condition No.</th>
<th>System Condition Q = 0.03 p.u., Varying P in p.u.</th>
<th>Fault duration (seconds)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.9</td>
<td>0.2</td>
</tr>
<tr>
<td>2</td>
<td>0.85</td>
<td>0.2</td>
</tr>
<tr>
<td>3</td>
<td>0.753</td>
<td>0.2</td>
</tr>
<tr>
<td>4</td>
<td>0.60</td>
<td>0.2</td>
</tr>
<tr>
<td>5</td>
<td>0.375</td>
<td>0.2</td>
</tr>
</tbody>
</table>

Fig. 7.2 System Response with Fuzzy Controlled SMES for system Condition 1, 2, 3, 4, 5
7.3.1.2 Transient Stability Investigations with Fuzzy controlled SMES for Different Fault Clearance Time

The effect of change of fault clearance time on the system response beyond the critical clearing time is indicated in Figs. 7.3 for a representative operating condition i.e. $P = 0.753$ p.u. and $Q = 0.03$ p.u. The system remains stable for fault clearance time up to $TFC = 0.25001$ seconds with Neuro-Fuzzy controlled SMES and becomes unstable with fault clearance time higher than 0.25001 seconds.

![Fig. 7.3 System Response with Fuzzy Controlled SMES for $P = 0.753$ p.u., $Q = 0.03$ p.u., for varying fault clearing time](image)

7.3.2 Transient Stability Investigation on Multi-machine System with Neuro-Fuzzy Controlled SMES

In order to examine the effectiveness of Neuro-Fuzzy logic based SMES on transient stability of multi-machine system, studies were carried out on a sample system considered in Fig.6.2 given in chapter 6.
The studies have been carried out for three phase symmetrical short circuit at the sending end of the transmission lines 3-4 and the fault is cleared by opening of the faulted line. Two Neuro-Fuzzy controllers are designed to obtain the estimated active power and reactive power. From P-SMES controller with which the system shows optimal dynamic performance is used as a training data for the Neuro-Fuzzy logic controller. For transient stability investigations, Neuro-Fuzzy logic based SMES controller is implemented taking into consideration the deviation in rotor relative angular velocity, $\Delta \omega$ and change in terminal voltage, $\Delta v$ as input variable to Neuro-Fuzzy controllers to obtain estimated active power $P_d$ and estimated reactive power $Q_d$.

Using Neuro-Fuzzy controlled SMES, the response curves are obtained for system considered for critical fault clearing time in the form variation of rotor angle $\delta_{31}$ and plotted in Fig. 7.4. System gets stabilized in approx. 2.0 seconds.

![Graph showing system response with and without Neuro-Fuzzy controlled SMES](image-url)

**Fig.7.4 System Response with Neuro-Fuzzy based SMES for Critical Fault Clearing Time**
7.4 Comparison of System Performance for P-SMES Control and Neuro-Fuzzy Controlled SMES

Transient stability investigation is carried out for two systems in the previous section. To study the effectiveness of Neuro-Fuzzy controlled SMES system performance is compared with that of P-SMES for both the systems.

7.4.1 Comparison of System Performance for P-SMES Control and Neuro-Fuzzy Controlled SMES for SMIB

The performance of system is investigated for two cases in the previous sections. To study the effectiveness of Neuro-Fuzzy controlled SMES system performance is compared with that of P-SMES for different loading conditions as well as for different fault clearance time.

7.4.1.1 Comparison of System Response for P-SMES Control and Neuro-Fuzzy Controlled SMES for SMIB for different Loading Conditions

Comparison of system response for different loading conditions given in Table 7.1 is investigated. System response i.e. variation of rotor angle $\delta$ is plotted in Figs. 7.5a–7.9a. It is observed that response of the system with Neuro-Fuzzy controlled is close to that of P-SMES in almost all the loading conditions. But for higher loading conditions it is better with Neuro-Fuzzy controlled SMES. The variation of corresponding performance index is plotted in Figs. 7.5b-7.9b and found close to that of with P-SMES in all the system conditions.
Fig. 7.5a System Response with P-SMES and Neuro-Fuzzy Controlled SMES for system condition 1

Fig. 7.5b Performance Index with P-SMES and Neuro-Fuzzy Controlled SMES for system condition 1
Fig. 7.6a System Response with P-SMES and Neuro-Fuzzy Controlled SMES for system condition 2

Fig. 7.6b Performance Index with P-SMES and Neuro-Fuzzy Controlled SMES for system condition 2
Fig. 7.7a System Response with P-SMES and Neuro-Fuzzy Controlled SMES for system condition 3

Fig. 7.7b Performance Index with P-SMES and Neuro-Fuzzy Controlled SMES for system condition 3
Fig. 7.8a System Response with P-SMES and Neuro-Fuzzy Controlled SMES for system condition 4

Fig. 7.8b Performance Index with P-SMES and Neuro-Fuzzy Controlled SMES for system condition 4
Fig. 7.9a System Response with P-SMES and Neuro-Fuzzy Controlled SMES for system condition 5

Fig. 7.9b Performance Index with P-SMES and Neuro-Fuzzy Controlled SMES for system condition 5
7.4.1.2 Transient Stability investigations with Neuro-fuzzy controlled SMES for different Fault Clearance Time

In this section, comparison of system response for different fault clearing time i.e beyond the critical clearing time is investigated. System performance i.e. variation of rotor angle $\delta$ is plotted in Figs. 7.10a – 7.12a. It is observed that response of the system with Neuro-Fuzzy controlled SMES is close to that of with P-SMES in all the conditions. The variation of corresponding performance index is plotted in Figs. 7.10b - 7.12b and found close to that of with P-SMES in all the system conditions.

![Graph showing system response with P-SMES and Neuro-Fuzzy controlled SMES](image)

Fig.7.10a System Response with P-SMES and Neuro-Fuzzy Controlled SMES for $P = 0.753$ p.u., $Q = 0.03$ p.u., $TFC = 0.21667$ secs
With P-SMES
With Neuro-fuzzy controlled SMES

Fig. 7.10b Performance Index with P-SMES and Neuro-Fuzzy Controlled SMES for $P = 0.753$ p.u., $Q = 0.03$ p.u., $TFC = 0.21667$ seconds

Fig. 7.11a System Response with P-SMES and Neuro-Fuzzy Controlled SMES for $P = 0.753$ p.u., $Q = 0.03$ p.u., $TFC = 0.23334$ seconds
Fig. 7.11b Performance Index with P-SMES and Neuro-Fuzzy Controlled SMES for $P = 0.753 \text{ p.u.}, Q = 0.03\text{ p.u.}, TFC = 0.23334$ seconds

Fig. 7.12a System Response with P-SMES and Neuro-Fuzzy Controlled SMES for $P = 0.753 \text{ p.u.}, Q = 0.03 \text{ p.u.}, TFC = 0.25001$ seconds
7.4.2 Comparison of Proportional type of SMES and Neuro-Fuzzy Controlled SMES for Multi-machine System for Critical Fault Clearing Time

The comparative study of swing curves corresponding to the best value of gain coefficient $k_m = 0.115$, $k_v = 0.05$ obtained so far and Neuro-Fuzzy controlled SMES is made in Fig. 7.13a for $TFC = 0.4244$ seconds. System performance i.e. variation of rotor angle $\delta_{31}$ is plotted in Figs. 7.13a. It is observed that response of the system with Neuro-Fuzzy controlled SMES is better than proportional type of SMES. The settling time of oscillations is less in case of Neuro-Fuzzy controlled SMES than that of Proportional type of SMES. The variation of corresponding performance index is plotted in Figs. 7.13b and found better with Neuro-Fuzzy controlled SMES.
Fig. 7.13a Comparison of System Response for Proportional-SMES and Neuro-Fuzzy Controlled SMES for Multi-machine system for $TFC = 0.4244$ seconds.

Fig. 7.13b Comparison of Performance Index for P-SMES and Neuro-Fuzzy Controlled SMES for Multi-machine System for $TFC = 0.4244$ seconds.
7.5 Comparison of Performance Index for P-SMES Control and Neuro-Fuzzy Controlled SMES for SMIB

In the previous sections, the system response with Neuro-Fuzzy controlled SMES is observed for two cases. Firstly, the active power output is varied from 0.375 p.u. to 0.9 p.u. Comparison of Performance Index for P-SMES control and Neuro-Fuzzy controlled SMES is given in Table 7.2 and plotted in Fig. 7.14. It is reflected from the table that Performance Index is better with Neuro-Fuzzy controlled SMES in almost all the cases. From Fig. 7.14 it is observed that with increase in the generator power output, the rate of increase of performance index is almost same with Neuro-Fuzzy controlled SMES and that of P-SMES.

Table 7.2: Comparison of Performance Index for varying Loading Conditions

<table>
<thead>
<tr>
<th>S.No.</th>
<th>System Condition Q=0.03, TFC = 0.2 secs</th>
<th>Performance Index for P-SMES</th>
<th>Performance Index for Neuro-Fuzzy Controlled SMES</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.375</td>
<td>2.5996</td>
<td>2.6000</td>
</tr>
<tr>
<td>2</td>
<td>0.6</td>
<td>6.3652</td>
<td>6.3534</td>
</tr>
<tr>
<td>3</td>
<td>0.753</td>
<td>9.8215</td>
<td>9.8011</td>
</tr>
<tr>
<td>4</td>
<td>0.85</td>
<td>12.4137</td>
<td>12.2011</td>
</tr>
<tr>
<td>5</td>
<td>0.9</td>
<td>14.0876</td>
<td>13.7932</td>
</tr>
</tbody>
</table>

Fig. 7.14 Comparison of Performance Index with different Pre-fault Loading Conditions
Secondly, the effect of variation of fault clearance time on system response of P-SMES is compared with Fuzzy controlled SMES. Comparison of performance index for varying fault clearance time is given in Table 7.3 for P-SMES control and Neuro-Fuzzy controlled SMES and plotted in Fig. 7.15. It is observed from the table that the rate of increase of Performance Index is less with Neuro-Fuzzy controlled SMES.

Table 7.3: Comparison of Performance Index for varying Fault Clearance Time

<table>
<thead>
<tr>
<th>S.No.</th>
<th>System Condition</th>
<th>Performance Index for P-SMES</th>
<th>Performance Index for Neuro-Fuzzy Controlled SMES</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>P=.753,Q=0.03 Varying TFC</td>
<td>9.8215</td>
<td>9.8011</td>
</tr>
<tr>
<td>2</td>
<td>0.21667</td>
<td>12.3121</td>
<td>12.1988</td>
</tr>
<tr>
<td>3</td>
<td>0.23334</td>
<td>15.2323</td>
<td>15.0487</td>
</tr>
<tr>
<td>4</td>
<td>0.25001</td>
<td>18.6865</td>
<td>18.6744</td>
</tr>
</tbody>
</table>

Fig. 7.15 Comparison of Performance Index with varying TFC
7.6 Conclusion

In this chapter the transient stability investigations have been carried out for two systems i.e. single machine to infinite bus system and multi-machine system, where Neuro-Fuzzy based SMES is used. Two Neuro-fuzzy controllers designed to obtain the estimated active power and reactive power.

For transient stability investigations for SMIB, Neuro-Fuzzy logic based SMES controller is implemented taking into consideration the deviation in rotor angle, \( \Delta \delta \), rotor relative angular velocity \( \Delta \omega \) for one of the Neuro-Fuzzy controller to obtain the estimated active power, whereas change in terminal voltage \( \Delta v \) and change in error in voltage \( \Delta v \), are taken as input variables to other Neuro-Fuzzy controller to obtain the estimated reactive power. For the training of the Neuro-Fuzzy controller data from the representative condition i.e. \( P = 0.753 \text{p.u.} \) and \( Q = 0.03 \text{p.u.} \) is taken. Neural network generates five membership functions for each input variable. 25 rules are generated for each Neuro-Fuzzy controller.

For transient stability investigations for multi-machine system, Neuro-Fuzzy logic based SMES controller is implemented taking into consideration the deviation in rotor relative angular velocity \( \Delta \omega \) and change in terminal voltage \( \Delta v \) for both of the Neuro-Fuzzy controller to obtain the estimated active power, and estimated reactive power. For the training of the Neuro-Fuzzy controller data from the \( TFC = 0.4244 \) secs. Neural network generates five membership functions for each input variable.

The performance of the system with Neuro-Fuzzy controller is investigated for different loading conditions as well as for varying fault clearing time for representative condition i.e. \( P = 0.753 \text{p.u.}, Q = 0.03 \text{ p.u.} \). The response of the system is compared with that of P-SMES. It is observed that the system response is better for higher loading conditions with Neuro-Fuzzy controller than that of P-SMES. Even with increased fault clearance time system response with Neuro-Fuzzy controlled SMES is very close to that of with P-SMES and to quantify the effectiveness of the Neuro-Fuzzy controlled SMES performance index is obtained and plotted. The performance index increases with increase in active power output with Neuro-Fuzzy controlled SMES as well as P-SMES. It is observed that with increase in the generator power output, the rate of increase of performance index is almost same with
Neuro-Fuzzy controlled SMES and that of P-SMES. Therefore, it may be concluded that Neuro-Fuzzy controlled SMES is able to provide better response than P-SMES for higher loading conditions.

System performance i.e. variation of rotor angle in case of multi-machine system for critical clearing time is plotted. It is observed that response of the system with Neuro-Fuzzy controlled SMES is better than proportional type of SMES. The settling time of oscillations is less in case of Neuro-Fuzzy controlled SMES than that of Proportional type of SMES. The variation of corresponding performance index is plotted and found better with Neuro-Fuzzy controlled SMES.