Design & Optimization of Intelligent PI Controllers (Fuzzy & Neuro-Fuzzy) for HVDC Transmission System

by

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AUTHOR’S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Munish Multani
This thesis deals with enhancing the performance of Fuzzy Logic (FL) based PI controllers for High Voltage Direct Current Transmission Systems (HVDC) by optimizing the key parameters i.e. membership functions (MFs) and fuzzy rule base in the controllers design.

In the first part of the thesis, an adaptive Fuzzy PI controller is designed and the effect of various MF shapes, widths and distribution on the performance of a FL controlled HVDC system under different system conditions is studied with the aim of selecting a MF which minimizes the total control error. Simulated results show that the shape, width and distribution of a MF influences the performance of the FL controller and concludes that nonlinear MFs (i.e. Gaussian) offer a more better choice than linear (i.e. Triangular) MFs as the former provides a smoother transition at the switching points and thus propose a better controller.

In the second part of the thesis, a Neuro-Fuzzy (NF) controller to update the fuzzy rule base with changing system conditions is proposed, which in turn adjusts the PI gains of a conventional PI controller. Results from simulations illustrate the potential of the proposed control scheme as the NF controller successfully adapts to different system conditions and is able to minimize the total current error.

**Keywords:** HVDC Converter, Fuzzy Logic Controller, Membership Function, Neuro-Fuzzy Controller, EMTP-RV
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NOMENCLATURE

$I_d$  DC current
$V_d$  DC Voltage
$P_d$  DC Power
$L_d$  Smoothing Reactor
$FL$  Fuzzy Logic
$NN$  Neural Network
$ANN$ Artificial Neural Network
$GA$  Genetic Algorithm
$MF$  Membership Function
$NF$  Neuro-Fuzzy
$\mu(x)$ Membership Function
$\epsilon$ Belong To
$\wedge$ Minimum
$FR$  Fuzzy Rule
$Min$  Minimum
$Max$ Maximum
$t$  T-Norm
$P$  Proportional Gain
$I$  Integral Gain
$pu$ per unit
$I_d \text{ (pu)}$ DC Current in per unit
I_{ref} (pu)  Reference DC Current in per unit

 e  Error

 Δe  Rate of Change of Error

 u  Controller Output

 K_p  Proportional Gain

 K_i  Integral Gain

 K_{p0}  Initial Value of Proportional Gain

 K_{i0}  Initial Value of Integral Gain

 k_p  Scaling Factor for Proportional Gain

 k_i  Scaling Factor for Integral Gain

 ΔK_p  Controller's Output for Proportional Gain

 ΔK_i  Controller's Output for Integral Gain

 T_r  Rise Time

 T_r  Settling Time

 % OS  Percentage Overshoot

 NB  Negative Big (Fuzzy Linguistic Variable)

 NM  Negative Medium (Fuzzy Linguistic Variable)

 NS  Negative Small (Fuzzy Linguistic Variable)

 ZE  Zero (Fuzzy Linguistic Variable)

 PS  Positive Small (Fuzzy Linguistic Variable)

 PM  Positive Medium (Fuzzy Linguistic Variable)

 PB  Positive Big (Fuzzy Linguistic Variable)

 SR  Smooth Recovery
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<td>S</td>
<td>Spike</td>
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<td>SSE</td>
<td>Steady State Error</td>
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<td>$W_i$</td>
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<td>IGBT</td>
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<td>IGCT</td>
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CHAPTER 1

General Background and Research Goals

1.1 Introduction

High Voltage Direct Current (HVDC) transmission is the preferred method for bulk power transmission over long distances as HVDC systems offer numerous advantages over AC transmission systems, such as:

- More power carrying capacity per conductor
- Asynchronous interconnection, therefore capable of connecting AC systems with different frequencies
- No skin effect, therefore resulting in lower transmission losses
- Less corona loss and interference with neighboring telephone systems
- DC links being more reliable, these systems improve transient stability and dynamic damping of electrical system oscillations.

But some issues such as high cost of converters, complexity of controls, inadequate performance when connected to weak AC systems, presence of harmonics, fewer number of DC lines in power systems, and use of flexible AC transmission systems
FACTS devices in AC transmission systems has restricted this technology to be used only in some particular transmission applications [1].

The transmitted power in a HVDC plant depends upon the efficacy of the closed loop control method being used. Therefore, the controller part of the system is the most important part but at the same time it is also the most complex part of the system for the following reasons:

- The dynamic performance of the HVDC plant varies with the strength of the connected AC system and other system conditions,
- The continual topological changes that occur within the AC system, affect the operating point of the controller,
- Converter transformer’s saturation characteristics and the use of AC/DC filters for harmonic elimination makes the whole system nonlinear and complex,
- Obtaining an accurate mathematical model of the system is not possible [2].

![Figure 1.1—Closed Loop Control Scheme for HVDC Plant](image-url)
Figure 1.1 shows the control scheme for the HVDC plant. Traditionally, PI controllers are used for the rectifier current control of the HVDC system, but due to fixed proportional (P) and integral (I) gains; these controllers can perform well only over a limited operating range. Therefore, HVDC systems are prone to repetitive commutation failure when connected to weak AC systems and also when subjected to faults and disturbances [3]. This leads to considerable research in the field of effective control of a HVDC systems using either adaptive, optimal, intelligent controllers such as fuzzy and neural networks, or embedded real time controllers [3, 4, 5, 8, 9, 10, 14, 15].

In recent years, a lot of interest has been shown in the application of intelligent control methods to the HVDC systems. Previous research focused on the development of FL controllers to adapt the gains of the conventional PI controller [3, 4, 5] as shown in Figure 1.2.

![Diagram](image)

Figure 1.2—Closed Loop Control Scheme with Fuzzy Logic for HVDC Plant
As this approach proved to be successful in improving the performance of the HVDC system, the focus shifted towards the optimization of the parameters of these controllers’ in order to further improve the performance of the system. In [6], the authors studied the effect of MFs of different shapes and concluded that there is different best performing MF for different fault conditions. Reference [7] uses Genetic Algorithm (GA) approach to tune the MFs of a fuzzy controller. Reference [8], experiments with the use of Neural Network (NN) based current controller to completely replace the conventional PI controller on the rectifier side.

This thesis deals with the optimization of the key parameters in the design of the FL controller i.e. MF and fuzzy rule base for further improvements. In the first part of the thesis, a FL controller is designed and tested with MFs of different shapes, width and distribution; objective being the selection of the best performing MF for a FL controlled HVDC system. In the second part of the thesis, principles of FL and Artificial Neural Network (ANN) are put together (Neuro-Fuzzy system) to propose a Neuro-Fuzzy (NF) controller to tune and update the fuzzy rule base with changing system conditions which in result adjusts the gains of conventional PI controller. The suggested work is implemented using EMTP-RV simulation package.

1.2 Research Motivation

HVDC is now a mature technology [1], starting from mercury-arc valves to thyristor’s and presently to IGBT (Integrated Gate Bipolar Transistors) and IGCT
(Integrated Gate Commutated Thyristors) valves, from conventional PI controllers to more advanced control techniques; further work needs to be done particularly on the control aspects to improve the transmission efficiency of such systems as the nonlinear and highly complex nature of the HVDC plant poses a challenge to control engineers.

Various control techniques based on adaptive and optimal control method [14, 15] have already been well researched. Previously, control techniques used assumed a fixed mathematical model of the plant but since HVDC systems are highly uncertain, obtaining an accurate mathematical model of the plant is not possible. Thus, there is a need for a control method or technique which

- Can operate well over a wide operating range,
- Can adapt to changing system conditions and parameters,
- Is insensitive to nonlinearities,
- Does not require mathematical model of the plant and
- Is simple to design and implement.

Intelligent control techniques such as FL, NNs and GAs in recent years have been shown to possess the above mentioned properties. These soft computing techniques have presented some promising results in various fields. In particular, FL techniques [3,4,5,9,10] have found themselves successful in the control of a HVDC system, but not much work has been done on the tuning of the FL controller’s parameters which may further improve the performance of the controller [6, 7]. Moreover, integration of ANN with FL has proved to be a powerful combination [31-39]. This is because, FL controllers
lack learning capability and may not be able to adapt with wide variations in the operating conditions. On the other hand, ANN controllers due to their learning ability are very adaptive but choice of these controllers is not viable for highly uncertain plants and also these controllers cannot handle data in the form of linguistic variables. Thus, combination of these two techniques into one system eliminates their individual drawbacks and such systems are termed as NF systems.

Overall, the motivation behind the work done in thesis can be attributed to the following reasons

- With the availability of some literature on the design of FL controller for the HVDC system, extensive work needs to be done on optimizing and tuning the parameters of these controllers.

- Furthermore, considerable amount of research work is required to test the feasibility of hybrid controllers such as NF controller for the HVDC systems.

Therefore this thesis is concerned with the design and optimization of intelligent controllers (particularly fuzzy and NF) for a HVDC system.

1.3 Problem Definition

High Voltage Direct Current (HVDC) transmission systems [1] traditionally employ PI controllers with fixed proportional (P) and integral (I) gains $K_p$ and $K_i$
respectively. Although such controllers are robust and simple, they are not easily optimized to obtain the best performance under all conditions because

- HVDC systems are highly nonlinear due to the components such as transformers, converter and filters.
- Harmonics generated by converters can interact with the controller.
- AC/DC filters can form resonant circuits with the power system.
- Obtaining an accurate mathematical model of the system is not possible.
- Sub-par performance when connected to weak AC systems.

Due to the fixed gains of conventional PI controller, these controllers are not able to perform well over a wide operating range. Therefore, this problem of fixed gains can be solved either by replacing these conventional controllers by some other control method or some methodology should be employed to update the PI gains with the change in operating point. As the power industry is very conservative on accepting new control techniques to replace existing PI controllers, thus optimizing and improving the performance of the existing controller is a more realistic approach and this partial addition of new control technique would be a step forward towards replacing the PI controller with a new and more efficient control method in coming years.

The proposed work deals with this problem of updating PI gains with change in system parameters by using FL based approach with the focus on tuning the parameters of these FL based controllers to obtain best results. Overall, intelligent controllers are being studied to see if they offer better alternatives.
1.4 Literature Review

Recently, FL Controllers [3, 4, 5] and NN controllers [8, 11, 12] have proved their potential for the control of HVDC system. Presently, active research is being carried out in optimizing the parameters of FL using GAs [7, 17, 18], and NNs [12].

In [3], authors developed a Hybrid controller (Fuzzy + PI) for the rectifier current control of a HVDC system. The gains of conventional PI controller are updated online around the initial values using the FL approach. During the transient period and under fault conditions the PI gains of the conventional PI controller are updated while during the steady state the controller works as fixed gain PI controller. The robustness of the proposed controller is tested for a three phase fault and 20% step change in current reference. A performance comparison between the two approaches i.e. Conventional and FL clearly shows the superiority of the FL technique.

In [10] FL approach is used to replace the Conventional Control scheme which refers to the selection of one of the two main control modes i.e. Constant Current (CC) mode which produces firing angle in order to minimize the total current error and the other being Constant Extinction Angle (CEA) mode which tries to keep extinction angle to its set (minimum) value. Each control mode has a separate PI controller with only one control mode selected at an instance of time. The proposed FL approach deals with the two major drawbacks of Conventional Control method:
• Sudden change from CC mode to CEA mode during transition period leads to abrupt changes controller’s parameters such as error, gains and time constants.

• As only one PI controller is selected at one point of time, the other PI controller saturates.

FL approach overcomes these problems by allowing a gradual transition from one control mode to the other. This is done by finding a composite error using FL methodology, which is the sum of the partial error from both the control modes. This error is applied to a PI controller, gains of which are also updated using FL. Since only one PI controller is used, the problem of saturation of controller is eliminated in this approach. The authors compare the performance of both the control methods i.e. Conventional Control method and FL based method under various different fault conditions. The results clearly show the superior performance of Fuzzy Logic approach over Conventional control method.

In [16], FL approach is used to adapt both Proportional and Integral gains of a conventional PI controller both at the rectifier and inverter ends of a HVDC system. The proposed controller is developed using current error and rate of change of error at the rectifier end while extinction angle error and its derivative for inverter side. The proposed controller gave better performance compared to fixed gain PI controller under various fault conditions. This paper established that it is better to tune the conventional PI controller in HVDC system rather than replacing it with control method which require a dynamic mathematical model of the system.
In [9], a performance comparison is made between FL approach for HVDC systems and other high performance controllers such as variable structure and self-tuning controllers. These controllers are designed and tested over a wide operating range. This paper concludes that a FL controller is a better choice over variable structure and adaptive controller as the former gives similar or better performance, and is very straightforward and easy to design as it does not require mathematical model of the plant unlike the other two.

In [4], the authors make a performance comparison between the FL controllers with different set of input parameters. Both the controllers are used to tune the PI gain of a conventional PI controller for a HVDC system. For one part, authors use current error and its derivative function to tune PI gains and in the second part, Lyapunov energy function and its derivative are taken as input to the FL controller to tune the proportional gain keeping the integral gain fixed. Both these controllers perform better than the conventional PI controller.

Reference [6], deals with optimization of FL controller’s parameters for more improved performance. This paper studied the effect of different MFs shapes on the performance of the HVDC system. Gaussian and Triangular MFs shapes are used as input to the FL controller. This paper concludes that for different fault conditions there is a different best performing MF. Overall, wide Gaussian MF is recommended for the HVDC system.
No literature can be found on the application of NF technology to HVDC system except [12] in which the authors combine the Radial Basis Function (RBF) NN with a fuzzy system, as both are functionally equivalent, to generate an adaptive current limit. The simulation results from various cases as studied in the publication clearly shows that the proposed NF VDCL controller has a potential to improve the performance of a HVDC system.

Publications [13], [31-39] show that NF techniques could offer some promising results. Reference [13] attends to the tuning problem of the FL controller. This is done by using NN and FL together to tune the MFs. FL architecture is interpreted as a NN. The error is propagated back through the network which in turn tunes the peak points of the MFs following the proposed learning algorithm. The proposed controller i.e. Proportional NF controller is trained offline using the training data, therefore it is best suited for applications where the desired output is known beforehand. Simulation and results clearly shows that proper tuning of FL controller leads to improved results. In [33], authors combine NN and FL to propose a Hybrid AI system for fault diagnosis in power systems. NN are used to indicate possibility of fault to occur while FL is used to show final results in linguistic form. Results show the effectiveness of the Hybrid system over NN based system. Reference [39] uses Neural-fuzzy approach for the control of highly nonlinear, time varying robotic manipulator system. In the proposed controller, the structure of the NN is kept intact and the same is used to implement fuzzy reasoning. In this approach MFs are first chosen randomly and then these are tuned by changing the weights of the NN using a self learning algorithm. The proposed controller is trained
offline in this case. Various simulation results provided show the effectiveness of the proposed control scheme.

1.5 Research Objectives and Contributions

This thesis deals with the application of intelligent control methods i.e. FL and NF to a HVDC system. Since control of a HVDC system is complex and poses many challenges, intelligent control methods provide a tool to easily and efficiently control the HVDC system which in turn leads to increased power transmission efficiency.

FL based PI controllers have already proven to be successful in the control of a HVDC system. Active research is being carried out in tuning the parameters of these controllers to further improve their adequacy. The proposed work tries to achieve this objective. In this thesis, first a FL controller to update PI gains of a conventional PI controller is designed in the simulation package EMTP-RV. This controller is tested with different MFs of various shapes, widths and distribution to find out the best performing MF for a HVDC system.

In the second part of this thesis, combination of NN and FL i.e. NF controller is proposed to control the HVDC system. This controller adds learning capability to the Fuzzy controller and updates the FL rule base with change in system parameters. In other words, tuning of the FL rule base is being done online. Furthermore, the key parameters of the proposed NF controller i.e. learning rate and momentum are also updated online
using FL approach. Robustness of the proposed controller is evaluated for test sequences such as step change in current order and three phase AC fault at the rectifier. This novel NF controller is designed in EMTP-RV simulation package.

### 1.6 Outline of the Thesis

This thesis consists of seven chapters. Chapter 1 introduces the problem and provides the background information and previous work done on this topic. Chapter 2 provides details of the HVDC transmission system under study which is modeled in EMTP-RV. Chapter 3 deals with the various aspects of design of the FL controller for HVDC system. Chapter 4 provides a detailed study of the effect of MFs of different shapes, width and distribution on the performance of the FL controlled HVDC system. Chapter 5 introduces NNs and NF systems. In Chapter 6, a NF controller for a HVDC plant is proposed. Different possible configurations of the proposed controller are studied. Simulation results show the robustness of the proposed controller under various faults and disturbances. These simulations are carried out in the EMTP-RV simulation package. Chapter 7 presents closing remarks and conclusions. The recommendations for future research are also provided to extend this research.
CHAPTER 2

HVDC Transmission System

2.1 Introduction

As this thesis deals with the study of intelligent control techniques for a HVDC transmission system, therefore, the test HVDC system used for the study is introduced in this chapter. The system consists of three subunits; each subunit along with its configuration is explained next.

2.2 System Description

Figure 2.1 represents the test HVDC system used. The system is modeled in EMTP-RV simulation package and is connected to an AC system having a Short Circuit Ratio (SCR) of 3.54. The SCR is defined as the ratio of short circuit power level at converter bus to the rated DC power. In this model, two 6-pulse converters are connected in series (bipolar 6-pulse converter) instead of a 12 pulse converter. In a real system, 12 pulse converters are used but bipolar 6-pulse converter is used here for simplicity and ease of computation.
The test system is composed of three sub-systems, as follows:

1) **Sub-system 1:**

A fixed R-L impedance (R = 0.25 ohms and L = 45 mH) between the generation source and the converter bus is used in this model. Two transformers with star-star and star-delta configuration are connected to each of the six pulse converters. The valve-side of both the transformers is ungrounded [20]. AC filters tuned to 11th, 13th, and high-pass frequencies are used on the AC side for harmonic elimination. In addition to this, AC filters are also used to provide reactive power required by the converter units as reactive power consumption of the converter changes with the change in load. Source voltage of 230 kV at 50 Hz is used for the AC side of the system.

2) **Sub-system 2:**

The DC side of the converter has a nominal voltage of 440 kV supplied by the inverter. The DC current is kept constant at 1600 A with nominal DC power ($P_d$) of 704 MW at the rectifier side. Two smoothing reactors at the rectifier side ($L_d = 350$ mH) are used to

- Remove any ripples present in the DC current,
- Provide protection from line surges,
- Limit the rate of increase of DC current; thus prevents any adverse effects of commutation failures in the converter.
A DC filter tuned to 12th harmonic is used to remove any harmonics present on the DC side.

3) **Sub-system 3:**

This part is the inverter DC system. The inverter is simply represented by fixed batteries of ± 220 kV with a diode in series. The diode prevents any back flow during a DC fault as the diode is reversed biased to the current flow during DC fault. RC snubbers (R = 1000 Ω and C = 0.1 μF) are also used in parallel with the diode. Here, the inverter side representation is simplified as the study focus is on the rectifier side, and its controller.

Figure 2.1—Six-pulse Bipolar HVDC System
2.3 Summary

In this chapter, the test HVDC system model used has been presented. Detailed description of each subsystem along with system parameters is provided.
CHAPTER 3

FUZZY LOGIC CONTROL

3.1 Introduction

FL control is based on fuzzy set theory. A fuzzy set is a set without a clear or well defined boundary unlike binary logic i.e. all elements of the fuzzy set belong to it to a certain degree given by the MF. A MF maps crisp input onto a normalized domain or fuzzy domain in the interval [0, 1] [21]. In recent years, FL systems have gained a lot of attention due to their ability to (1) incorporate expert (human originated) knowledge into the system design which can be very useful in making correct decisions and carrying out appropriate control actions and (2) effectively handle imprecise, ambiguous and incomplete information [22, 23].

FL systems are rule based or knowledge based systems. Expert knowledge or designer’s knowledge about the system to be controlled is stored in the knowledge base as simple IF-THEN rules and this knowledge base is used by fuzzy controller to deduce appropriate control action using an inference mechanism, Compositional Rule of Inference is used in general.
Overall, FL controller acts as a buffer between a nonlinear, highly complex system and desired control output, offering numerous advantages such as providing a model free approach, allowing human intelligence to be included in the control scheme and ability to perform any nonlinear control action as fuzzy systems are universal approximators [24].

### 3.2 Basics of Fuzzy Logic Control

The design of FL controller consists of four basic stages i.e. **Fuzzification, Fuzzy Rule Base, Inference Engine and Defuzzification** as shown in Figure 3.1.

![Figure 3.1 — Block Diagram of a Fuzzy Logic Controller](image)
Before discussing the basic stages of the FL controller it is necessary to include a brief description of linguistic variables and linguistic values.

3.2.1 Linguistic Variables & Values

In our day to day communications, we explain things in approximate or general terms for example “Munish is tall”, “the library is far away” even if we knew that “Munish is 6 feet tall” and “the library is 400 m away” but we prefer linguistic terms rather than numerical numbers to convey the information. Fuzzy systems consist of a knowledge base comprising of fuzzy IF-THEN rules developed by human experts who prefer to use linguistic terms to describe the behavior of the system. Therefore there is a need for “linguistic variables and values” to specify fuzzy systems inputs, outputs and rule base. For example, let us consider the following fuzzy rule

**IF** error is large **THEN** output is high

Here “error”, “output” represent linguistic variables and “large”, “high” represents the corresponding linguistic values. Hence, linguistic variables can be said to be the variables which are described in terms of words instead of numbers and the values assumed by these variables which describe their characteristics are termed as linguistic values [25].
### 3.2.2 Fuzzification

Fuzzification is the first step in the design of a FL controller and it refers to the process of transforming a crisp or real valued variable into a fuzzy variable. Fuzzification is carried out by using the *membership function* which maps every crisp element in the universe onto a fuzzy interval \([0, 1]\). Therefore, MF gives the degree to which a certain element belongs to the fuzzy set.

Consider a fuzzy set ‘H’ for hot room temperature given by equation (3.1) and represented by Figure 3.2.

\[
H = \{(x, \mu_H(x)) | x \in X, \mu_H(x) \in [0, 1]\}
\]  

(3.1)

Where, ‘x’ is crisp input, ‘X’ represents the universe and \(\mu_H(x)\) gives the membership value.

![Membership Function (\(\mu_H(x)\)) for Hot Room Temperature](image)

Figure 3.2—Membership Function (\(\mu_H(x)\)) for Hot Room Temperature
Now for every crisp input we will get a corresponding membership value (linguistic value) as shown by the above graph. Assume that the room temperature is measured as 20°C which is neither hot nor cold. So according to the MF of Hot, this input will have a fuzzy output between 0 and 1, but more close to 1 i.e. more possibility of it being hot. If an element has a membership value of ‘0’ it means that element does not belong to the fuzzy set, a membership value of ‘1’ shows the element surely belongs to the fuzzy set and a value between 0 and 1 gives the possibility of element belonging to the fuzzy set.

As the process of fuzzification is accomplished using MFs, therefore, to design an efficient controller, it becomes very important for the designer to:

1. Carefully decide on the number of fuzzy sets (MFs) required for system input(s)/output(s) which corresponds to number of fuzzy rules,
2. Make an appropriate choice of the shape (linear or nonlinear), width (narrow, medium or wide) and distribution (linear or polynomial distribution) of the MFs.

A detailed study on the influence of MFs on the performance of the controller is provided in the next chapter.

3.2.3 Fuzzy Rule Base

Fuzzy rule base can be considered as the heart of the FL controller as it contains all the information necessary to control the plant or system under study. Therefore, the objective of the FL controller to make intelligent or humanlike decisions is achieved by
the fuzzy rules which guide the controller towards a correct control action. Fuzzy rule base is comprised of individual IF-THEN fuzzy rules of the form

\[ \text{FR: IF } e \text{ is A THEN } y \text{ is B} \]

Where ‘e’ is the crisp input from the process, ‘y’ is the fuzzy output and A, B represents the linguistic values for the linguistic variable e and y respectively. As can be seen, fuzzy rule can be divided into two parts i.e. IF (antecedent) THEN (consequent) where antecedent part defines the condition and consequent part gives the corresponding control action [25].

The number of rules in a rule base depends on the number of input and output variables and on the number of MFs attached to each variable. Let us take the example of a two input, one output system. If each input has five MFs (fuzzy sets) attached to it then we will have a rule base comprising of 5 * 5 i.e. 25 rules of the form:

\[ \text{FR}_1: \text{IF } e \text{ is NB and } \Delta e \text{ in PB THEN } y \text{ is PB} \]

else

\[ \text{FR}_2: \text{IF } e \text{ is PB and } \Delta e \text{ in PB THEN } y \text{ is NB} \]

else

......

\[ \text{FR}_{25}: \text{IF } e \text{ is NB and } \Delta e \text{ in NM THEN } y \text{ is PM} \]
Where e, ∆e represents the crisp input from the process, y is the fuzzy output and NB (negative big), PB (positive big), PM (positive medium) represents the linguistic values. The *else* acts as a connective to join individual rules in the rule base.

Overall, the fuzzy rule base provides the platform to include expert knowledge or human intelligence into the control system.

### 3.2.4 Fuzzy Implication

Fuzzy implication refers to the method or procedure of deducing a meaningful interpretation or influence of each if-then rule comprising a fuzzy rule base. Thus, fuzzy implication leads to a fuzzy output for each activated rule. There are several methods of fuzzy implication such as:

- Larsen Implication
- Mamdani Implication
- Zadeh Implication
- Dienes-Rescher Implication
- Lukasiewicz Implication

Out of these, *Larsen (product)* and *Mamdani (min)* implication methods are most popular and commonly used and are explained below:

\[
FR_i: \textbf{IF} \ e \ \text{is} \ A_i \ \text{and} \ \Delta e \ \text{in} \ B_i \ \textbf{THEN} \ y \ \text{is} \ C_i
\]
\[ \mu_{FR_i}(a, b, c) = t(\mu_{Ai}(a), \mu_{Bi}(b)) \ast \mu_{Ci}(c) \]

\[ = \mu_{Ai}(a) \ast \mu_{Bi}(b) \ast \mu_{Ci}(c) \text{(Larsen)} \quad (3.2) \]

\[ \mu_{FR_i}(a, b, c) = t(\mu_{Ai}(a), \mu_{Bi}(b)) \land \mu_{Ci}(c) \]

\[ = \mu_{Ai}(a) \land \mu_{Bi}(b) \land \mu_{Ci}(c) \text{(Mamdani)} \quad (3.3) \]

Where, \( FR_i \) represent the \( i^{th} \) fuzzy rule of the rule base consisting of \( n \) (\( i = 1, ..., n \)) number of rules, 't' represents the T-norm operator and equation (3.2) and (3.3) give the fuzzy output for the \( i^{th} \) rule using Larsen and Mamdani implication method respectively. It should be noted here that any T-norm operator (product or minimum) can be used for computing the antecedent part of the fuzzy rule for both Larsen and Mamdani implications. In this thesis product is used for all T-norm operators in case of Larsen implication and min is used for all T-norm operators in case of Mamdani implication.

Fuzzy implication gives the output of each individual rule in the rule base but in order to reach to a correct control output, combined effect of entire rule base is required to be computed. As crisp measurement from the process (input) will be a part of more than one MF (fuzzy set) therefore it will result in activating a number of rules in the fuzzy rule base. Thus, to compute the influence of entire rule base i.e. to infer the fuzzy control output; compositional rule of inference is used which can be applied in two ways i.e. (1) Composition using individual rules, (2) Composition using entire rule base.
Composition using individual rule is most commonly used for the design of a FL controller and this is the one used in this thesis. The following section explains this method of inference.

3.2.4.1 Composition using individual rules

For description of such an inference method, let us assume a fuzzy rule base consisting of ‘n’ number of rules of the form:

\[
\text{FR}_i: \text{IF } e \text{ is } A_i \text{ and } \Delta e \text{ is } B_i \text{ THEN } y \text{ is } C_i
\]

Here, \( i \) represent the \( i^{th} \) rule of the rule base.

Now, to compute the output of the entire rule base, the following steps are followed:

1. Membership value for the antecedent part of the rule base is calculated which is given as

\[
\mu_{FRi}(a, b) = t(\mu_{Ai}(a), \mu_{Bi}(b))
\]  \hfill (3.4)

2. Influence of antecedent part on the consequent part of the rule is computed which is given as

\[
\mu_{FRi}(a, b, c) = t(\mu_{Ai}(a), \mu_{Bi}(b), \mu_{Ci}(c))
\]  \hfill (3.5)
Here, \( t \) represents the T-norm operator which is *product* for Larsen implication and *min* for Mamdani implication.

(3) After performing steps (1) & (2) for each individual rule, output of each rule is aggregated using aggregation operator (sum or max) to deduce a final fuzzy output value for the process.

Hence for crisp inputs \( a_0 \) and \( b_0 \), control output is given as

\[
\mu_c'(c) = \max_{1 \leq i \leq n} \ t(\mu_{Ai}(a_0), \mu_{Bi}(b_0), \mu_{Ci}(c))
\]  
(3.6)

\[
\mu_c'(c) = \sum_{i=1}^{n} t(\mu_{Ai}(a_0), \mu_{Bi}(b_0), \mu_{Ci}(c))
\]  
(3.7)

Where, max, sum represent the aggregation operators and ‘t’ signifies the T-norm operator. Therefore equation (3.7) for Larsen and Mamdani implication can be written as equations (3.8) and (3.9) respectively.

\[
\mu_c'(c) = \sum_{i=1}^{n} (\mu_{Ai}(a_0) \ast \mu_{Bi}(b_0) \ast \mu_{Ci}(c))
\]  
(3.8)

\[
\mu_c'(c) = \sum_{i=1}^{n} \min(\mu_{Ai}(a_0), \mu_{Bi}(b_0), \mu_{Ci}(c))
\]  
(3.9)
3.2.5 Defuzzification

The control output obtained after the inference mechanism is fuzzy in nature, but a crisp value is required at the output of the FL controller to control the system under study. Therefore, the technique which converts the fuzzy output of the controller into its corresponding crisp value is known as defuzzification. There are many types of defuzzification methods available such as centre of gravity, mean of maxima and threshold method. However, centre of gravity defuzzification method is chosen for the design of the fuzzy logic controller in this thesis. The reasons which lead to the choice of this method are:

(1) It is fairly simple and requires less computational time and effort.

(2) This method takes into account each and every activated rule of the fuzzy rule base as sum operator is used unlike other methods using max operator in which the rule with highest value of the MF is considered for the output [25].

For crisp inputs $a_0$ and $b_0$ the corresponding crisp control output $c'$ using centre of gravity defuzzification is given by the following equation

$$c' = \frac{\sum_{i=1}^{n} c'_i \ t(\mu_{Ai}(a_0), \mu_{Bi}(b_0), \mu_{Ci}(c))}{\sum_{i=1}^{n} t(\mu_{Ai}(a_0), \mu_{Bi}(b_0))} \quad (3.10)$$

Where, $c'_i$ represents the centre of the output fuzzy set. Since, singleton MFs are used for the output, therefore $\mu_{Ci}(c) = 1$ i.e. normalized, therefore equation (3.10) can be written as follow:
\[
\sum_{i=1}^{n} c_i' = \frac{\sum_{i=1}^{n} t(\mu_{A_i}(a_0), \mu_{B_i}(b_0))}{\sum_{i=1}^{n} t(\mu_{A_i}(a_0), \mu_{B_i}(a_0))}
\]  
(3.11)

For Larsen and Mamdani implication centre of gravity defuzzification is given by equations (3.12) and (3.13) respectively.

\[
\sum_{i=1}^{n} c_i' = \frac{\sum_{i=1}^{n} c_i' \mu_{A_i}(a_0) \mu_{B_i}(b_0)}{\sum_{i=1}^{n} (\mu_{A_i}(a_0) \mu_{B_i}(b_0))}
\]  
(3.12)

\[
\sum_{i=1}^{n} c_i' = \frac{\sum_{i=1}^{n} \min(\mu_{A_i}(a_0), \mu_{B_i}(b_0))}{\sum_{i=1}^{n} \min(\mu_{A_i}(a_0), \mu_{B_i}(b_0))}
\]  
(3.13)

### 3.3 Design of Adaptive Fuzzy PI controller

Traditionally, PI controllers are used for the control of a HVDC system but these controllers do not perform well during severe faults, large disturbances or when HVDC system is connected to a weak AC system. The reason for a deteriorated performance is that the fixed proportional (P) and integral (I) gains are optimized only for a small operating range and thus the system may suffer from repetitive commutation failures and substandard performance with a sudden change in the operating conditions. This problem can be taken care of either by updating the gains of a conventional PI controller with changing system conditions or by replacing PI controllers with a new control scheme. In this thesis, the method of updating PI gains using a FL scheme is chosen. The proposed controller is named as *Adaptive Fuzzy PI Controller.*
FL control systems consist of four parts i.e. **Fuzzification, Fuzzy rule base, Fuzzy inference engine and Defuzzification**. Figure 3.3 shows block diagram of a FL controller as built in EMTP-RV with nine rules. This figure is an example figure for clarity purposes only; in reality a much more detailed FL controller with 49 rules is chosen.

### 3.3.1 Fuzzification

As discussed earlier, fuzzification is a process of converting crisp values to the fuzzy values. Since, MFs are used to convert crisp inputs into its fuzzy values therefore, seven Gaussian MFs with a Universe of Discourse \([-1, 1]\) are used for both input and output.

As seen in Figure 3.3, error and rate of change of error are taken as inputs. Both the inputs are normalized so that they fall within the range of Universe of Discourse and these normalized inputs are connected to the fuzzification block, consisting of MFs which are implemented in EMTP using look-up tables as seen in the Figure 3.3. A number of MFs with different shapes, size and distribution are tested and are discussed in the next chapter.

### 3.3.2 Fuzzy Rule Base

Fuzzy rule base [22] acts as the central component of the FL controller as it gives the designer a platform to store all the information necessary to control the plant whether
Figure 3.3 — Fuzzy Logic Controller with three MFs and nine rules in EMTP-RV
it comes from the designer itself or an expert operator. Therefore, it can be considered as a brain of the FL controller as FL controller can make decisions by itself looking at the rule base. For example, if the output is far off from a set point, the rule base will guide the controller to apply a larger control action in the opposite direction in order to move the output toward the reference value.

In the proposed work, a rule base comprising of 49 rules is used which corresponds to two inputs fuzzified using seven MFs. Since we are updating proportional and integral gains of the conventional PI controller, therefore rule base used to update proportional and integral gains is given by Tables 3.1 and 3.2 respectively [3].

**TABLE 3.1**
Rule Base For $\Delta K_p$

<table>
<thead>
<tr>
<th>$e/\Delta e$</th>
<th>NB</th>
<th>NM</th>
<th>NS</th>
<th>ZE</th>
<th>PS</th>
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<td>PM</td>
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<td>ZE</td>
<td>NS</td>
<td>ZE</td>
<td>PB</td>
<td>PB</td>
<td>PB</td>
</tr>
<tr>
<td>PB</td>
<td>ZE</td>
<td>NS</td>
<td>NM</td>
<td>ZE</td>
<td>PB</td>
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</tr>
</tbody>
</table>

**TABLE 3.2**
Rule Base For $\Delta K_i$

<table>
<thead>
<tr>
<th>$e/\Delta e$</th>
<th>NB</th>
<th>NM</th>
<th>NS</th>
<th>ZE</th>
<th>PS</th>
<th>PM</th>
<th>PB</th>
</tr>
</thead>
<tbody>
<tr>
<td>NB</td>
<td>NB</td>
<td>NB</td>
<td>NB</td>
<td>NB</td>
<td>NM</td>
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<td>NB</td>
<td>NB</td>
<td>NM</td>
<td>NS</td>
<td>ZE</td>
<td>PS</td>
</tr>
<tr>
<td>NS</td>
<td>NB</td>
<td>NB</td>
<td>NM</td>
<td>NS</td>
<td>ZE</td>
<td>PS</td>
<td>PM</td>
</tr>
<tr>
<td>ZE</td>
<td>NB</td>
<td>NM</td>
<td>NS</td>
<td>ZE</td>
<td>PS</td>
<td>PM</td>
<td>PB</td>
</tr>
<tr>
<td>PS</td>
<td>NM</td>
<td>NS</td>
<td>ZE</td>
<td>PS</td>
<td>PM</td>
<td>PB</td>
<td>PB</td>
</tr>
<tr>
<td>PM</td>
<td>NS</td>
<td>ZE</td>
<td>PS</td>
<td>PM</td>
<td>PB</td>
<td>PB</td>
<td>PB</td>
</tr>
<tr>
<td>PB</td>
<td>ZE</td>
<td>PS</td>
<td>PM</td>
<td>PB</td>
<td>PB</td>
<td>PB</td>
<td>PB</td>
</tr>
</tbody>
</table>
3.3.3 Fuzzy Inference Engine

The Larsen Inference Engine is used as it is both simple and powerful amongst the various other implication operators. It is given as

$$
\mu_{R_i}(e, \Delta e, u) = \mu_{A_i}(e) \ast \mu_{B_i}(\Delta e) \ast \mu_{C_i}(u)
$$

(3.14)

Where, e, \(\Delta e\) represents the error and rate of change of error respectively, and u is the output. \(\mu_{A_i}(e)\), \(\mu_{B_i}(\Delta e)\) represents the membership value corresponding to the crisp input and \(\mu_{C_i}(u)\) represents fuzzified control action.

Mamdani inference engine was also employed and tested for some cases but no significant difference in the performance of the FL controller was observed.

3.3.4 Defuzzification

Centre Average Defuzzifier is used for both the Larsen and Mamdani engines. The crisp output is given by

$$
\begin{align*}
    u(e, \Delta e) &= \frac{\sum_{i=1}^{n} u_i \mu_{A_i}(e) \ast \mu_{B_i}(\Delta e)}{\sum_{i=1}^{n} \mu_{A_i}(e) \ast \mu_{B_i}(\Delta e)} \quad \text{(For Larsen)} \\
    u(e, \Delta e) &= \frac{\sum_{i=1}^{n} \min \{ \mu_{A_i}(e) \mu_{B_i}(\Delta e) \}}{\sum_{i=1}^{n} \min \{ \mu_{A_i}(e) \mu_{B_i}(\Delta e) \}} \quad \text{(For Mamdani)}
\end{align*}
$$

(3.15) (3.16)
Where \( u(e, \Delta e) \) is the crisp output and \( u'_i \) represents the centre of the output MF.

### 3.3.5 FL + PI Controller

The output of the FL controller is used to solve the problem of fixed Proportional and Integral gains of a conventional PI controller i.e. PI gains are updated online using the FL controller, as shown in Figure 3.4, and according to the following equations:

\[
K_p = K_{p0} + k_p \Delta K_p
\]  
(3.17)

\[
K_i = K_{i0} + k_i \Delta K_i
\]  
(3.18)

Where \( K_{p0} \) and \( K_{i0} \) represent initial proportional and integral gains, \( \Delta K_p, \Delta K_i \) give outputs of the FL controller and \( k_p, k_i \) symbolize scaling factors of the controller.

The following steps explain the working and tuning of the proposed adaptive FL controller:

1. The initial values of the proportional and integral gains i.e. \( K_{p0} \) and \( K_{i0} \) of the conventional PI controller are found using trial and error (tuned to best performance).
2. Current error and rate of change of this error are taken as inputs to the FL controller. These inputs are normalized and then fuzzified using MFs. Then,
these fuzzified inputs are applied to the rule base. The rule bases for finding $\Delta K_p$ and $\Delta K_i$ are summarized using Tables 3.1 and 3.2 respectively. Since output obtained through an aggregation of the individual rules is fuzzy in nature, defuzzification is carried out using centre average defuzzifier to obtain crisp values of $\Delta K_p$ and $\Delta K_i$. These values are then used to update gains of the conventional PI controller.

(3) The output from the FL controller can be scaled using the scaling factors $k_p$ and $k_i$. Therefore, initial values of $K_{p0}$ and $K_{i0}$ gains used are usually set to lower values than what is obtained in step 1 so that the FL controller adapts to the appropriate gain values by itself.

(4) Scaling factors of the controller are tuned to obtain the best possible performance.

Figure 3.4—Fuzzy Logic based PI controller
3.4 Simulation & Results

To test the effectiveness of the proposed controller, the HVDC system is subjected to the following test sequences:

(1) Step Changes in Current Order (30% and 50%)
(2) Three Phase Fault at Rectifier (50 ms and 100 ms)

Both the FL and conventional PI controller are simulated in EMTP-RV and the results are compared for the above mentioned system disturbances.

3.4.1 Step Change in Current Order (30% and 50%)

A step change of 30% and 50% is applied to the reference current. From the simulated results (Figure 3.5), it is clear that for a 30% step change, both the controllers perform well but the FL controller gives a better transient performance and quite a low overshoot as compared to the conventional PI controller.

For a large disturbance of 50% change in current order, conventional PI controller suffers from commutation failure and does not recover well (Figure 3.6). The reason for the failure of PI controller may be attributed to the fixed PI gains as with fixed gains controller can perform well only over a small operating range and therefore, with abrupt change in operating conditions, the controller suffers from commutation failure. On the
other hand FL controller is able to recover quite well which shows the potential of the proposed controller.

Figure 3.5—Response of PI and FL Controller to 30% Step Change

Figure 3.6—Response of PI and FL Controller to 50% Step Change

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### 3.4.2 Three Phase Fault at Rectifier (100 ms and 50 ms)

For a 5 cycle (100 ms) 3 phase fault, the FL controller shows better transient performance in terms of lower spikes and better traceability when compared to a conventional PI controller. For a 2.5 (50 ms) cycle fault, conventional PI controller fails as the system suffers from repetitive commutation failures most likely due to the fixed PI gain. While on the other hand the system is able to recover well with a FL controller, although it suffers from one commutation failure. Figure 3.7 and 3.8 show responses of both FL and PI controllers to 100 ms and 50 ms 3-phase fault respectively.

![Figure 3.7—Response of PI and FL Controller to 3-Phase Fault (100 ms)](image-url)
3.4 Summary

In this chapter theory of fuzzy logic has been introduced. The four building blocks of the FL control i.e. fuzzification, fuzzy rule base, fuzzy inference engine and defuzzification were discussed. Adaptive Fuzzy PI controller to tune the PI gains of a conventional PI controller is proposed for a HVDC plant. Detailed design of the proposed controller in EMTP-RV is presented along with its methodology. Simulated results are provided for both the controllers under different fault conditions.
CHAPTER 4

INFLUENCE OF SHAPE, WIDTH & DISTRIBUTION OF MFs

4.1 Introduction

A MF is a key parameter in the design of a FL controller. The controller performance can be further improved by a judicious choice of the MF, the implication operator, the aggregation operator and the defuzzification method. As the fuzzy rule base is characterized by MFs, an appropriate choice is vital. Previous work on the use of FL control for HVDC plants relied on basic triangular MFs with 50% overlap and linear distribution for the fuzzification of the input. Hence, there is a need to study the effect of different MF shapes, width and distribution on the performance of a FL controlled HVDC system [2].

This chapter discusses the effect of different MFs shapes (Triangular, Trapezoidal, Gaussian, Two-sided Gaussian and Bell), width (Narrow, Medium and Wide) and distribution (Linear or Polynomial) on the performance of the proposed FL controller. The objective of this study is to find out up to what extent MFs of different shapes, width
and distribution influence the performance of the FL controller when controlling the HVDC system and which MF shape and distribution gives best performance.

### 4.2 Influence of Shape, Width & Distribution of Membership Functions (MFs)

A number of MFs (Table 4.1) with different shapes, size and distribution are tested. These MFs were initially built using Matlab code and then implemented into EMTP-RV through look-up tables. Brief details of the various MFs used are presented next.

#### 4.2.1 Triangular MF

A built in function “trimf” in Matlab is used.

\[
\mu_T = \text{trimf}(x, [a \ b \ c])
\]  

(4.1)

Where \(a\), \(b\), \(c\) are the breakpoints of the MF with \(b\) representing the centre. The parameters ‘\(a\)’ and ‘\(c\)’ are used to vary the width. Figure 4.1 shows seven triangular MFs with 50% overlap over a Universe of Discourse [-1, 1].
Figure 4.1—Triangular Membership Function

<table>
<thead>
<tr>
<th>Name</th>
<th>MF Shape</th>
<th>Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>MF1</td>
<td>Triangular</td>
<td>Narrow</td>
</tr>
<tr>
<td>MF2</td>
<td>Trapezoidal</td>
<td>Narrow</td>
</tr>
<tr>
<td>MF3</td>
<td>Gaussian</td>
<td>Narrow</td>
</tr>
<tr>
<td>MF4</td>
<td>Two-Sided Gaussian</td>
<td>Narrow</td>
</tr>
<tr>
<td>MF5</td>
<td>Bell</td>
<td>Narrow</td>
</tr>
<tr>
<td>MF6</td>
<td>Triangular</td>
<td>Medium</td>
</tr>
<tr>
<td>MF7</td>
<td>Trapezoidal</td>
<td>Medium</td>
</tr>
<tr>
<td>MF8</td>
<td>Gaussian</td>
<td>Medium</td>
</tr>
<tr>
<td>MF9</td>
<td>Two Sided Gaussian</td>
<td>Medium</td>
</tr>
<tr>
<td>MF10</td>
<td>Bell</td>
<td>Medium</td>
</tr>
<tr>
<td>MF11</td>
<td>Triangular</td>
<td>Wide</td>
</tr>
<tr>
<td>MF12</td>
<td>Trapezoidal</td>
<td>Wide</td>
</tr>
<tr>
<td>MF13</td>
<td>Gaussian</td>
<td>Wide</td>
</tr>
<tr>
<td>MF14</td>
<td>Two-Sided Gaussian</td>
<td>Wide</td>
</tr>
<tr>
<td>MF15</td>
<td>Bell</td>
<td>Wide</td>
</tr>
<tr>
<td>MF16</td>
<td>Triangular</td>
<td>Polynomial Distribution</td>
</tr>
<tr>
<td>MF17</td>
<td>Trapezoidal</td>
<td>Polynomial Distribution</td>
</tr>
<tr>
<td>MF18</td>
<td>Gaussian</td>
<td>Polynomial Distribution</td>
</tr>
</tbody>
</table>
4.2.2 Trapezoidal MF

The Matlab function “trapmf” is used.

\[
\mu_{\text{Trap}} = \text{trapmf}(x, [a \ b \ c \ d]) \quad (4.2)
\]

Where a, b, c, d are the breakpoints of the MF. Here, parameters ‘a’ and ‘d’ are used to vary the width of the MF. Figure 4.2 shows trapezoidal MFs with medium width.

![Figure 4.2—Trapezoidal Membership Function](image)

4.2.3 Gaussian MF

This is built using the Matlab function “gaussmf”

\[
gaussmf(x, [\sigma \ c]) = e^{-\frac{(x-c)^2}{2\sigma^2}} \quad (4.3)
\]
\[ \mu_{\text{Gauss}} = \text{gaussmf}(x, [\sigma \ c]) \]  \hspace{1cm} (4.4)

Where “c” represents centre and “\(\sigma\)” is used to vary the width of the MF. MFs with \(\sigma = 0.07, 0.14\) and \(0.238\) are used.

Figure 4.3—Gaussian Membership Function

4.2.4 Two-Sided Gaussian MF

This is obtained by combining two Gaussian MFs giving more control on varying the width of the function. In Matlab code it is given by “gauss2mf”

\[ \mu_{\text{Gauss2mf}} = \text{gauss2mf}(x, [\sigma_1 \ c_1 \ \sigma_2 \ c_2]) \]  \hspace{1cm} (4.5)
With $\sigma_1 c_1$ represents width and centre of leftmost curve and rightmost curve is represented using $\sigma_2 c_2$. Two sided Gaussian MF with medium width is shown in the following figure.

![Two sided Gaussian Membership Function](image)

**Figure 4.4—Two-sided Gaussian Membership Function**

### 4.2.5 Bell MF

This is built using Matlab function “gbellmf” which is implemented as follows

$$\mu_{bell} = gbellmf(x,[a \ b \ c])$$

(4.6)

Where,

$$gbellmf(x,[a \ b \ c]) = \frac{1}{\left(1+ABS\left(\frac{x-c}{\sigma}\right)\right)^{2b}}$$

(4.7)
Where, a, b, c represent the parameters which decide the width of the MF and its position over the Universe of Discourse.

![Bell Membership Function](image)

**Figure 4.5—Bell Membership Function**

### 4.2.6 MFs with Polynomial Distribution

Polynomial distribution [25] of MFs results in higher density of MFs near the origin of domain. The MFs as shown in Figures 4.1-4.5 have a linear distribution as the MFs are equally distributed over the whole Universe of Discourse. Now, if we increase the density of MFs near the origin of domain i.e. increase the number of MFs at origin, the controller is expected to provide finer output for small error i.e. when error is close to zero. The Gaussian, Triangular and Trapezoidal MFs are used to test the performance of the system with such a distribution and Figure 4.6 gives an example of polynomial distribution with triangular MFs.
To the best knowledge of the author, Polynomial Distribution of the MFs for a FL controlled HVDC system is tested for the first time in this work.

![Membership Functions with Polynomial Distribution](image)

**Figure 4.6—Membership Functions with Polynomial Distribution**

### 4.3 Simulation & Results

To study the impact of the MFs of varying shape, width and distribution, the performance of the HVDC system is evaluated for test sequences such as step change in current order and three phase AC fault at the rectifier. MFs used for this study are summarized in Table 3.1. The results are also compared with those of the conventional PI controller.
4.3.1 Step Change in Current Order (30% and 50%)

The stability and response of the controller is tested by applying step changes of 30% and 50% to the reference value. The performance of the FL controller for these disturbances is evaluated for each of the MF as listed in Table 3.1. Figures 4.7 & 4.8 shows the response of FL controller with Triangular MF (of varying width and distribution) to 30% and 50% step changes respectively. Similarly, Figures 4.9 – 4.16 present simulation results for FL controller with Trapezoidal, Gaussian, two sided Gaussian and Bell MFs.

The results for each of the MF in terms of rise time ($T_r$), % overshoot (%OS) and settling time ($T_s$) are summarized in Tables 4.2 and 4.3 for 30% and 50% step changes in current order respectively.

From the results, it is clear that for a step change of 30% MF11, MF13, MF14, MF15 (Wide category) and MF9 (Medium category) gives lower overshoot than all the other MFs. MF16 (Polynomial Distribution) performs even worse than the conventional PI controller with high overshoot and ringing while MF17 and MF18 performs quite well. It is also observed that polynomial distribution (MF 16, 17 & 18) has lower rise time ($T_r$) and narrow category of MFs (MF1-MF5) results in lowest settling time ($T_s$).
Figure 4.7—Response of Triangular MF to 30% Step Change

Figure 4.8—Response of Triangular MF to 50% Step Change
Figure 4.9—Response of Trapezoidal MF to 30% Step Change

Figure 4.10—Response of Trapezoidal MF to 50% Step Change
Figure 4.11—Response of Gaussian MF to 30% Step Change

Figure 4.12—Response of Gaussian MF to 50% Step Change
Figure 4.13—Response of 2-Sided Gaussian MF to 30% Step Change

Figure 4.14—Response of 2-Sided Gaussian MF to 50% Step Change
Figure 4.15—Response of Bell MF to 30% Step Change

Figure 4.16—Response of Bell MF to 50% Step Change
For a large disturbance, such as 50% step change, conventional PI controller fails to recover but adaptive fuzzy PI controller, with any choice of MF, is able to recover well and without a commutation failure occurring. All the MFs belonging to Wide and Medium category, except trapezoidal (MF7 and MF12), recover smoothly with acceptable overshoot. High overshoot with ringing is observed for some MFs but no commutation failure (CF) is observed for any of the eighteen MFs used.

### TABLE 4.2
30% Step Change in Current Order

<table>
<thead>
<tr>
<th>MF</th>
<th>$T_r$ (ms)</th>
<th>%OS</th>
<th>$T_s$ (ms)</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>MF1</td>
<td>10.7</td>
<td>8.6</td>
<td>41.2</td>
<td>SR</td>
</tr>
<tr>
<td>MF2</td>
<td>10.8</td>
<td>8.2</td>
<td>41.3</td>
<td>SR</td>
</tr>
<tr>
<td>MF3</td>
<td>10.9</td>
<td>7.4</td>
<td>41.3</td>
<td>SR</td>
</tr>
<tr>
<td>MF4</td>
<td>10.7</td>
<td>8.7</td>
<td>41.3</td>
<td>SR</td>
</tr>
<tr>
<td>MF5</td>
<td>10.1</td>
<td>7.4</td>
<td>41.3</td>
<td>SR</td>
</tr>
<tr>
<td>MF6</td>
<td>10.6</td>
<td>8.4</td>
<td>60.2</td>
<td>SR</td>
</tr>
<tr>
<td>MF7</td>
<td>10.7</td>
<td>8.5</td>
<td>61.5</td>
<td>SR</td>
</tr>
<tr>
<td>MF8</td>
<td>11.1</td>
<td>7.7</td>
<td>64.5</td>
<td>SR</td>
</tr>
<tr>
<td>MF9</td>
<td>13.4</td>
<td>6.5</td>
<td>84.5</td>
<td>SR</td>
</tr>
<tr>
<td>MF10</td>
<td>10.9</td>
<td>7.8</td>
<td>57.8</td>
<td>SR</td>
</tr>
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<td>MF11</td>
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<td>MF12</td>
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<td>8.5</td>
<td>61.5</td>
<td>SR</td>
</tr>
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<td>13.3</td>
<td>6.5</td>
<td>81.8</td>
<td>SR</td>
</tr>
<tr>
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<td>10.3</td>
<td>6.5</td>
<td>81.8</td>
<td>SR</td>
</tr>
<tr>
<td>MF15</td>
<td>13.4</td>
<td>6.5</td>
<td>81.8</td>
<td>SR</td>
</tr>
<tr>
<td>MF16</td>
<td>10.1</td>
<td>24.8</td>
<td>177.7</td>
<td>OS with ringing</td>
</tr>
<tr>
<td>MF17</td>
<td>10.2</td>
<td>8.7</td>
<td>92.5</td>
<td>SR</td>
</tr>
<tr>
<td>MF18</td>
<td>10.3</td>
<td>9.1</td>
<td>73.5</td>
<td>SR</td>
</tr>
<tr>
<td><strong>PI</strong></td>
<td><strong>12.9</strong></td>
<td><strong>11.81</strong></td>
<td><strong>76.3</strong></td>
<td><strong>SR</strong></td>
</tr>
</tbody>
</table>

*T_r* = Rise Time; OS = Overshoot; $T_s$= Settling Time; SR = Smooth Recovery
### TABLE 4.3
50% Step Change in Current Order

<table>
<thead>
<tr>
<th>MF</th>
<th>$T_r$ (ms)</th>
<th>% OS</th>
<th>$T_s$ (ms)</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>MF1</td>
<td>13.6</td>
<td>29.8</td>
<td>127.6</td>
<td>No CF, High OS with Ringing</td>
</tr>
<tr>
<td>MF2</td>
<td>13.7</td>
<td>14.5</td>
<td>75.1</td>
<td>No CF, SR</td>
</tr>
<tr>
<td>MF3</td>
<td>13.6</td>
<td>30.4</td>
<td>191.3</td>
<td>No CF, High OS with Ringing</td>
</tr>
<tr>
<td>MF4</td>
<td>13.7</td>
<td>14.5</td>
<td>71.7</td>
<td>No CF, SR</td>
</tr>
<tr>
<td>MF5</td>
<td>13.8</td>
<td>30.4</td>
<td>190.6</td>
<td>No CF, High OS with Ringing</td>
</tr>
<tr>
<td>MF6</td>
<td>13.5</td>
<td>14.5</td>
<td>90.8</td>
<td>No CF, No ringing</td>
</tr>
<tr>
<td>MF7</td>
<td>13.5</td>
<td>31.3</td>
<td>194.3</td>
<td>No CF, High OS with Ringing</td>
</tr>
<tr>
<td>MF8</td>
<td>13.6</td>
<td>14.6</td>
<td>71.3</td>
<td>No CF, SR</td>
</tr>
<tr>
<td>MF9</td>
<td>13.7</td>
<td>11.5</td>
<td>84.7</td>
<td>No CF, SR</td>
</tr>
<tr>
<td>MF10</td>
<td>13.6</td>
<td>14.5</td>
<td>71.3</td>
<td>No CF, SR</td>
</tr>
<tr>
<td>MF11</td>
<td>15.1</td>
<td>14.4</td>
<td>101.3</td>
<td>No CF, SR</td>
</tr>
<tr>
<td>MF12</td>
<td>13.5</td>
<td>31.3</td>
<td>198.1</td>
<td>No CF, High OS with Ringing</td>
</tr>
<tr>
<td>MF13</td>
<td>13.8</td>
<td>11.8</td>
<td>97.6</td>
<td>No CF, SR</td>
</tr>
<tr>
<td>MF14</td>
<td>13.7</td>
<td>11.5</td>
<td>91.5</td>
<td>No CF, SR</td>
</tr>
<tr>
<td>MF15</td>
<td>13.9</td>
<td>10.7</td>
<td>91.5</td>
<td>No CF, SR</td>
</tr>
<tr>
<td>MF16</td>
<td>11.4</td>
<td>28.6</td>
<td>154.6</td>
<td>High OS with ringing</td>
</tr>
<tr>
<td>MF17</td>
<td>13.9</td>
<td>30.5</td>
<td>180.3</td>
<td>High OS with ringing</td>
</tr>
<tr>
<td>MF18</td>
<td>11.6</td>
<td>29.6</td>
<td>194.3</td>
<td>High OS with ringing</td>
</tr>
<tr>
<td>PI</td>
<td>32.8</td>
<td>34.64</td>
<td>H</td>
<td>(CF) &amp; (Recovery with H)</td>
</tr>
</tbody>
</table>

*CF = Commutation Failure; OS = Overshoot; SR = Smooth Recovery; H = Harmonics
4.3.2 Three Phase Fault at Rectifier (100 ms & 50 ms)

A 3-phase fault is created at the rectifier AC bus for periods of 5 cycles (100 ms) and 2.5 cycles (50 ms). During the 3-phase fault there is a commutation failure due to which DC current drops to zero with firing angle at its maximum value. Therefore, the fault leads to the complete collapse of DC link due to zero current and zero power transfer. Hence, the controller comes into play only when the fault is cleared. Once the fault is cleared, the controller should be able to follow the reference quickly i.e. controller should have a very short response time.

Figures 4.17-4.26 shows the response of FL controller to 5 cycle and 2.5 cycle three phase faults for each of the eighteen MFs used.

![Figure 4.17—Response of Triangular MF to 3-Phase Fault (100 ms)](image-url)
Figure 4.18—Response of Triangular MF to 3-Phase Fault (50 ms)

Figure 4.19—Response of Trapezoidal MF to 3-Phase Fault (100 ms)
Figure 4.20—Response of Trapezoidal MF to 3-Phase Fault (50 ms)

Figure 4.21—Response of Gaussian MF to 3-Phase Fault (100 ms)
Figure 4.22—Response of Gaussian MF to 3-Phase Fault (50 ms)

Figure 4.23—Response of 2-Sided Gaussian MF to 3-Phase Fault (100 ms)
Figure 4.24—Response of 2-Sided Gaussian MF to 3-Phase Fault (50 ms)

Figure 4.25—Response of Bell MF to 3-Phase Fault (100 ms)
Figure 4.26—Response of Bell MF to 3-Phase Fault (50 ms)

From the simulation results, it is noted that Fuzzy-PI controller, with any choice of MF, follows the Voltage Dependent Current Limit (VDCL) ramp much better than a conventional PI controller. For a 5 cycle fault, it is observed that Fuzzy-PI controller is able to reduce the oscillations during the recovery i.e. have a better transient performance than the conventional PI controller. It is also observed that medium and wide category of membership functions (MF6 - MF15) performs slightly better than narrow ones.

For a 2.5 cycle fault, conventional PI controller suffers from repetitive commutation failures and is not able to recover. Most of the MFs belonging to narrow category (MF1, MF3 – MF5) have a poor recovery but MFs having medium and large
width perform better except (MF 7, MF10 & MF12). MF17 has the worst performance with very high steady state error.

**TABLE 4.4**  
Three Phase 5 Cycles Fault (100 ms)

<table>
<thead>
<tr>
<th>MF</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>MF1</td>
<td>Good Recovery (S =0.35 pu)</td>
</tr>
<tr>
<td>MF2</td>
<td>Good Recovery (S =0.31 pu)</td>
</tr>
<tr>
<td>MF3</td>
<td>Good Recovery (S =0.36 pu)</td>
</tr>
<tr>
<td>MF4</td>
<td>Good Recovery (S =0.33 pu)</td>
</tr>
<tr>
<td>MF5</td>
<td>Good Recovery (S =0.33 pu)</td>
</tr>
<tr>
<td>MF6</td>
<td>Better Recovery than narrow MFs(S =0.45 pu)</td>
</tr>
<tr>
<td>MF7</td>
<td>Better Recovery than narrow MFs (S =0.33 pu)</td>
</tr>
<tr>
<td>MF8</td>
<td>Better Recovery than narrow MFs (S =0.43 pu)</td>
</tr>
<tr>
<td>MF9</td>
<td>Better Recovery than narrow MFs (S =0.63 pu)</td>
</tr>
<tr>
<td>MF10</td>
<td>Better Recovery than narrow MFs (S =0.33 pu)</td>
</tr>
<tr>
<td>MF11</td>
<td>Better Recovery than narrow MFs (S =0.43 pu)</td>
</tr>
<tr>
<td>MF12</td>
<td>Better Recovery than narrow MFs (S =0.33 pu)</td>
</tr>
<tr>
<td>MF13</td>
<td>Better Recovery than narrow MFs (S =0.63 pu)</td>
</tr>
<tr>
<td>MF14</td>
<td>Better Recovery than narrow MFs (S =0.63 pu)</td>
</tr>
<tr>
<td>MF15</td>
<td>Better Recovery than narrow MFs (S =0.45 pu)</td>
</tr>
<tr>
<td>MF16</td>
<td>Good Recovery (S =0.49 pu)</td>
</tr>
<tr>
<td>MF17</td>
<td>Good Recovery (S =0.43 pu)</td>
</tr>
<tr>
<td>MF18</td>
<td>Good Recovery (S =0.43 pu)</td>
</tr>
<tr>
<td>PI</td>
<td>Good Recovery (S =0.71 pu)</td>
</tr>
</tbody>
</table>

*S = Spike
4.4 Summary

In this chapter, the key parameter in the design of a FL controller i.e. the choice of the MF is dealt with. A FL based PI controller is tested with eighteen different choices of

---

**TABLE 4.5**

Three Phase 2.5 Cycles Fault (50 ms)

<table>
<thead>
<tr>
<th>MF</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>MF1</td>
<td>1 CF with High SSE and large $T_s$</td>
</tr>
<tr>
<td>MF2</td>
<td>Recovers late but good recovery.</td>
</tr>
<tr>
<td>MF3</td>
<td>1 CF with High SSE and large $T_s$</td>
</tr>
<tr>
<td>MF4</td>
<td>1 CF with High SSE and large $T_s$</td>
</tr>
<tr>
<td>MF5</td>
<td>1 CF with High SSE and large $T_s$</td>
</tr>
<tr>
<td>MF6</td>
<td>1 CF but good recovery.</td>
</tr>
<tr>
<td>MF7</td>
<td>1 CF with High SSE and large $T_s$</td>
</tr>
<tr>
<td>MF8</td>
<td>1 CF but good recovery.</td>
</tr>
<tr>
<td>MF9</td>
<td>1 CF but good recovery.</td>
</tr>
<tr>
<td>MF10</td>
<td>1 CF with High SSE and large $T_s$</td>
</tr>
<tr>
<td>MF11</td>
<td>1 CF but good recovery.</td>
</tr>
<tr>
<td>MF12</td>
<td>1 CF with High SSE and large $T_s$</td>
</tr>
<tr>
<td>MF13</td>
<td>1 CF but good recovery.</td>
</tr>
<tr>
<td>MF14</td>
<td>1 CF but good recovery.</td>
</tr>
<tr>
<td>MF15</td>
<td>1 CF but slightly better recovery.</td>
</tr>
<tr>
<td>MF16</td>
<td>1 CF but good recovery.</td>
</tr>
<tr>
<td>MF17</td>
<td>1 CF with Very High SSE</td>
</tr>
<tr>
<td>MF18</td>
<td>1 CF but good recovery.</td>
</tr>
<tr>
<td>PI</td>
<td>Repetitive CF</td>
</tr>
</tbody>
</table>

*SSE = Steady state error; CF = Commutation Failure*
MFs to find out up to what extent shape, width and distribution of MFs affects the performance FL controlled HVDC system and to provide designers with more choice of the MFs other than basic triangular MF. The performance of the FL controller with each of the MF in terms of rise time, settling time and overshoot for step change and three phase fault conditions has been provided in tabular form along with simulation results for each of the MF.
CHAPTER 5

NEURAL NETWORKS & NEURO-FUZZY SYSTEMS

5.1 Introduction

In the field of intelligent control systems, Fuzzy Logic Control and Artificial Neural Network based Control are the two most popular control methodologies being used. In case of FL approach major advantages are (1) it does not require accurate mathematical model of the plant, only general knowledge about the plant is enough to use fuzzy control, (2) the ability of the controller to incorporate knowledge about the plant in the form of simple if-then rules i.e. it offers simple representation of knowledge and (3) the capability of the controller to deduce an appropriate control action by itself using a simple inference mechanism. On the other hand, NN based controllers are highly efficient in learning any kind of nonlinearity [21, 26]. These controllers are highly adaptive and their parallel architecture leads to lower computational time and hence faster response. In addition to this, both FL and NN are universal approximators [24, 27].
The likelihood of having more intelligent and efficient control technique by combining the advantages of both FL and NNs together leads to the concept of NF systems. Many publications on these neuro-fuzzy systems show the potential of such systems [31-39].

In this chapter, NF systems are introduced which lays the foundation for the proposed neuro-fuzzy controller for the HVDC system as discussed in the next chapter. Since NF systems are combination of both NN and FL, therefore a brief introduction to NNs is considered necessary.

5.2 Artificial Neural Networks (ANNs)

The ability of the human brain to learn, perceive, motor control and generalize inspired research in the field of Artificial Neural Networks [28]. The human nervous system consists of billions of neurons connected to each other through dendrites. Each neuron acts as a processing element which combines all the inputs connected to it and if this value exceeds the firing threshold of the neuron, it generates an output signal.

ANNs are the computational systems having the same basic concept as that of human nervous system. Figure 5.1 shows mathematical model of the neuron which is the building block of the NN.
Here, $X_1, X_2, \ldots, X_n$ represents the input signals to the neuron, $W_0$ firing threshold, $F(\cdot)$ the nonlinear activation function and the output $y$ of the neuron is given as

$$y = F \left( \sum_{i=1}^{n} W_i X_i + W_0 \right) \quad (5.1)$$

A number of such neurons when joined together; form a network known as an artificial neural network (ANN). The arrangement of these neurons in a NN from input to output layer leads to different neural network architectures; the feedforward and the recurrent architectures being the most commonly used. In this thesis, a four layer feedforward network is used, as will be discussed next.
5.2.1 The Feedforward Architecture

Figure 5.2 represents a feedforward NN with two inputs and one output. In a feedforward network, the output of the neurons in one layer acts as the input to the neurons of the following layer; with no feedback connection present in the network. This topology is chosen as (1) it is similar to FL architecture with two inputs and one output and hence can be combined to form a NF system; (2) learning algorithms such as steepest descent, can be conveniently used with such network architecture.

![Feedforward Artificial Neural Network Architecture with two inputs one output](image)

Figure 5.2— Feedforward Artificial Neural Network Architecture with two inputs one output
5.3 Neuro-Fuzzy Systems

Neuro-Fuzzy systems, as the name suggests combine ANNs and FL into one system. The aim of such a combination is to inherit advantages of both the intelligent control techniques and shunt out their individual disadvantages. FL Controllers are easy to design and implement, have the power of representing knowledge in the form of simple if-then rules using linguistic variables, do not require a mathematical model of the plant, are robust, flexible etc but these controllers have a major drawback of not having any learning capability. Hence, these controllers are not adaptive which leads to use of trial and error method for tuning of its parameters such as MFs and rule base.

On the other hand, ANN based controllers are capable of handling any kind of nonlinearity quite efficiently. Their strengths include huge parallelism offered by these controllers and their ability to learn. Moreover, these controllers are highly adaptable as connection weights can be updated with changing system conditions and this adaptation of weights can be done online by using some learning algorithm or offline by training the network with training data. But these controllers suffer from drawbacks such as NN controllers once trained act as a black box and it is not possible to extract or add any information to these trained NNs, slow convergence of learning algorithm and inability to deal with information in linguistic form [21].
Overall, the NF systems have the learning ability, adaptability which is missing in FL controller. Furthermore, these systems, unlike NNs, have the capability of dealing with both numerical and linguistic data.

In this thesis, a novel hybrid neuro-fuzzy system is used to tune the PI gains of a conventional PI controller in a HVDC system as done by the fuzzy PI controller in chapter 3. This is done to see if this system offers a better alternative. The following section explains the architecture of hybrid neuro-fuzzy system used followed by implementation of the proposed controller to the HVDC system in the next chapter.

5.4 Architecture of Hybrid Neuro-Fuzzy System Used

A 2–input, 1–output, 4–layered NF system is used as shown in Figure 5.3. This network can be viewed as either a FL system or a four layered ANN as both are functionally equivalent. If viewed as a NN, each layer of the network corresponds to a particular FL operation from fuzzification to defuzzification. As seen from the figure below, Layer 1 acts as fuzzification layer; layer 2 contains the fuzzy rules with Layers 3 and 4 acting as consequent and defuzzification layers respectively.

This network is much more effective than the FL or NN alone as it has the advantages of both. Due to the incorporation of FL into NN, the resulting network has the benefits of parallelism, simple representation of data in terms of linguistic variables in
the hidden layers, and the learning ability. Layer by layer description of the network is as follow:

![Figure 5.3— Hybrid NF System Architecture with 2-inputs and 1-output [21]](image)

5.4.1 Layer 1

This layer acts as fuzzification layer. Each node of this layer contains a MF (fuzzy set) and the number of nodes in this layer depends on the number of fuzzy sets associated with each of the inputs. The output of each node is the fuzzified value of the crisp input
applied to it. Any choice of MF can be used for fuzzification but it should be differentiable as steepest descent learning algorithm requires a differentiable function. The fuzzy output of this layer forms the input to Layer 2 which is explained next.

5.4.2 Layer 2

This layer stores the fuzzy if-then rules. Each node in this layer represent the IF part of each rule and the number of rules depends on the number of inputs and number of fuzzy sets associated with each input. Product or \( \text{min} \) T-norm operators are generally used to calculate the firing strength of each rule i.e. the output of each node.

5.4.3 Layer 3

Each node of this layer contains the output fuzzy sets i.e. the consequent part of the rule base. Generally, singleton fuzzy sets are used for the output. This layer computes the output of each rule using either Larsen or Mamdani implication, and infers the controllers output from the entire rule base using the compositional rule of inference.

In addition to this, the sum of the firing strengths of each rule is also calculated. The output of each node of this layer is connected to each node in the next layer.
5.4.4 Layer 4

This layer consist of just one node which implements the centre of average defuzzification method to convert the fuzzy output from Layer 3 to the crisp output which forms the output of the NF system. The output is calculated by dividing the output from the Layer 3 by the sum of the strength of each rule which is also computed in Layer 3.

5.5 Summary

In this chapter, NNs and NF systems have been introduced. Hybrid NF architecture has been discussed in detail layer by layer which provides the basics for the proposed NF controller to be discussed in the next chapter.
CHAPTER 6

NEURO-FUZZY PI CONTROL OF A HVDC SYSTEM

6.1 Introduction

Fuzzy Logic (FL) based controllers have been successful in improving the performance of the HVDC system as discussed in Chapters 3 and 4. A FL control scheme is used to adapt gains of the conventional PI controller with changing system conditions, thus solving the problem of fixed PI gains in a conventional control scheme. But, the optimization of these controllers is still a part of ongoing research.

A NF controller which combines ANN with FL to inherit advantages of both is proposed in this chapter. The ANN adds learning capability, parallelism and generalization to FL systems [29]. The proposed NF controller optimizes the fuzzy rule base to achieve the desired performance. In addition to the tuning problem, the FL based PI controller has the task of finding the correct initial values of PI gains as adaptation is done around these initial values. On the other hand, the NF controller, because of its
learning ability, is capable of self-learning the gain values without the need for any initial values, thereby adding more flexibility to the controller.

The NF controller is constructed using two different feedforward network architecture’s i.e. RBF (Radial Basis Function) and CMAC (Cerebellar Model Articulation Controller Networks) [30]. This is done (1) to see which one offers better performance and (2) to reinforce the work done in [2] as the former uses the Gaussian MF (non-linear) and the latter uses the Triangular MF (Linear).

In addition to this, FL approach is also used for the online adaptation of the key parameters of NF controller i.e. learning rate ($\eta$) and momentum ($\mu$), hence making the controller completely self-regulating. This proposed novel controller is built using EMTP-RV simulation package, for evaluation purposes.

6.2 Neuro-Fuzzy Controller using EMTP-RV

A 4-layer hybrid NF system is presented (Figure 6.2). The architecture can be considered as a parallel architecture because each layer of the FL system corresponds to a particular layer of ANN and vice versa. Therefore, the resulting network can be viewed as either an ANN or a FL system with only difference that the hidden layer of ANN acts as the inference system [21]. Each layer of the 4-layer NF controller is described next.
6.2.1 Layer 1

This layer fuzzifies the normalized input variables according the following equation:

\[ \mu_{A'}(a) = \mu_A(a_0); \mu_{B'}(b) = \mu_B(b_0) \]  \hspace{1cm} (6.1)

Where \( a_0, b_0 \) are crisp input values from a process and \( \mu_A(a), \mu_B(b) \) are the corresponding membership values. Three MFs with a Universe of Discourse \([-1, 1]\) are used for both input and output. Figure 6.1 presents the MFs used, as explained below.

6.2.1.1 Triangular MF

For CMAC architecture, triangular MF is used which is built using the “trimf” function in Matlab. This is shown below:

\[ \mu_T = \text{trimf}(x, [a \ b \ c]) \]  \hspace{1cm} (6.2)

Where \( a, b, c \) are the breakpoints of the MF with \( b \) representing the centre.

6.2.1.2 Gaussian MF

This is used for RBF architecture and built using the Matlab function “gaussmf” as given below:
\[ gaussmf(x, [\sigma c]) = e^{\frac{-(x-c)^2}{2\sigma^2}} \]  
\[(6.3)\]

\[ \mu_{\text{Gauss}} = gaussmf(x, [\sigma c]) \]  
\[(6.4)\]

Where “c” represents centre and “\(\sigma\)” is used to vary the width of the MF. A MF with \(\sigma = 0.4124\) is used.

![Membership Functions Used](image)

These MFs are first built using Matlab and then implemented in EMTP-RV using look up tables, as shown in Figure 6.2.

### 6.2.2 Layer 2

This layer contains the antecedent part of the fuzzy rule base. Each node in this layer is connected to the nodes of the previous layer. The proposed controller has three
Figure 6.2 — Hybrid Neuro-Fuzzy System Architecture with 2-inputs and 1-output implemented in EMTP-RV
nodes in Layer 1 which correspond to nine nodes in Layer 2 i.e. nine rules. The output of the nodes in this layer gives the strength of each rule using a T-norm operator which is \textit{product} (more local) for the proposed controller [21] and is implemented in EMTP-RV using a product block, as shown in Figure 6.2. The output of the neurons in Layer 2 is given by the following equation:

\[ o_{l_{2i}}(e, \Delta e) = \mu_{A_i}(e) \ast \mu_{B_i}(\Delta e) \]  \hspace{1cm} (6.5)

Where, \(e, \Delta e\) are the error and rate of change of error inputs respectively, \(\mu_{A_i}(e), \mu_{B_i}(\Delta e)\) represents the membership value corresponding to the crisp input and \(o_{l_{2i}}(e, \Delta e)\) gives the output of each node in Layer 2. Here, ‘i’ denote the number of nodes, which also corresponds to the number of rules.

### 6.2.3 Layer 3

The consequent (\textit{then}) part of the rule base is given by this layer. This part of the Rule Base is updated to reach the minimum error value. Singleton fuzzy sets are used for the output i.e. membership grade is ‘1’ at a particular centre value or ‘0’ otherwise, as given by the following equation:

\[ \mu_{C_i}(c) = 1; \quad \text{for } c = w_{c_i} \]

\[ 0; \quad \text{otherwise} \]  \hspace{1cm} (6.6)
where, $w_{ci}$ represents the centre value of the output fuzzy set.

![Output MFs (Singleton)](image)

Figure 6.3— Output MFs (Singleton)

The output of each node in this layer of NF controller is given by the following equation:

$$o_{l3i}(e, \Delta e) = o_{l2i}(e, \Delta e) \ast w_{ci}$$  \hspace{1cm} (6.7)

Where, $e, \Delta e$ denotes the error and rate of change of error inputs respectively. $o_{l2i}(e, \Delta e)$ gives the output of each node in Layer 2, $w_{ci}$ represents the centre of the output fuzzy set in terms of FL theory or connection weight in terms of ANN.

Here, $o_{l2i}(e, \Delta e)$ is also equivalent to the Larsen implication for each rule as
shown below:

\[ \mu_{c_i'}(e, \Delta e, w_{c_i}) = (\mu_{A_1}(e) \cdot \mu_{B_1}(\Delta e) \cdot \mu_{C_1}(w_{c_i})) \] (Larsen implication for each rule) \hspace{1cm} (6.8)

\[ = o_{t_{2i}}(e, \Delta e) \quad \because \mu_{C_1}(w_{c_i}) = 1 \] \hspace{1cm} (6.9)

Furthermore, weights or centers of output MF \((w_{c_i})\) are being updated using the steepest descent learning algorithm. This adjustment of weights has been carried out in the following two ways:

(1) Weights are updated in a continuous manner but within the Universe of Discourse and,

(2) Tuning of weights around fixed values, obtained from the fuzzy rule base.

This layer also consists of another unit which computes the sum of the strengths of each rule fired, as given by the following equation:

\[ o_{t_{3a}}(e, \Delta e) = \sum_{i=1}^{n} o_{t_{2i}}(e, \Delta e) \] \hspace{1cm} (6.10)

6.2.4 Layer 4

The input to this layer is the output of the Layer 3. Defuzzification is carried out by this layer to get the crisp output. Centre average defuzzifier is used whose output is given as:
\[ u(e, \Delta e) = \frac{\sum_{i=1}^{n} a_{i3}(e, \Delta e)}{\sum_{i=1}^{n} a_{i3a}(e, \Delta e)} \]  
\[ = \frac{\sum_{i=1}^{n} w_{ci} \mu_{A_i}(e) \mu_{B_i}(\Delta e)}{\sum_{i=1}^{n} \mu_{A_i}(e) \mu_{B_i}(\Delta e)} \]  

Where, \( u(e, \Delta e) \) denotes the crisp output of the NF controller.

### 6.3 Learning Algorithm

Weights in Layer 3 are updated in order to minimize the square of the error given by the following equation using the Delta Rule.

\[ E = \sum_{i=1}^{1} \left( o_d - o_a \right)^2 \]  

Where, \( o_d \) gives the desired output and \( o_a \) represents the actual output of the system.

The Gradient Descent law of learning is given by the following equation:

\[ \Delta w_i = -\eta \frac{\partial E}{\partial w_i} \]  

Where, \( \eta \) gives the learning rate of the network.
Weights are updated as follows:

\[ \Delta w_i(t + 1) = w_i(t) + \Delta w_i \]  

(6.15)

Where,

\[ \Delta w_i = \eta \cdot (o_d - o_a) \cdot \frac{o_2(e, \Delta e)}{\sum o_2(e, \Delta e)} \]  

(6.16)

Unwanted oscillations due to a large learning rate (\( \eta \)) and low speed due to small learning rate can be avoided by adding momentum (\( \mu \)) to the learning algorithm [21], according to the following equation:

\[ \Delta w_i(t + 1) = \Delta w_i + \mu \cdot \Delta w_i(t) \]  

(6.17)

The attractiveness of this learning algorithm lies in the fact that the NN is trained online and therefore it does not require any training data.

### 6.4 Methodology

Figure 6.2 shows the 2-input and 1-output proposed NF controller as built in EMTP-RV. Error, which is the difference between the actual and desired output (generated by VDCL), and rate of change of error are taken as inputs. The step by step behavior of the proposed controller is discussed next.
The inputs to Layer 1 are the normalized values of error and rate of change of error. Layer 1 performs the process of fuzzification using Triangular and Gaussian MFs for CMAC and RBF architectures respectively.

(2) The output of Layer 1 is fed to Layer 2 which consists of antecedent part of the rule base. As product is used as T-norm operator, output of Layer 2 is the product of the fuzzified inputs for each node,

(3) Layer 3 acts as a computational layer as weight adjustment is done in this layer. In other words, consequent part of the rule base is updated using the well known Delta Rule which is a gradient descent method of learning. The weights are adjusted either continuously over the Universe of Discourse or tuned around fixed centre values obtained from fuzzy rule base,

(4) Defuzzification using centre average defuzzifier is carried out in Layer 4. The output of this layer being crisp in nature is the final output of the NF controller. This output is used to adapt PI gains of the conventional PI controller as discussed in the next section.

### 6.4.1 Continuous Adjustment of Weights

The weights are adjusted continuously with time according to the following equation:

\[
\Delta w_i(t + 1) = w_i(t) + \Delta w_i
\]  

(6.18)
Here, $w_i(t)$ gives the weight value or centre value at time $t$, $\Delta w_i(t + 1)$ gives the updated weight value and $\Delta w_i$ denotes the change in weight value given by equation (6.16).

In this method, limits have to be put so that the updated weight values remain within the Universe of Discourse. For the proposed NF controller, the continuous weight adjustment works fine and there is no need of limits but still a limiter has been used for precautionary reasons. The advantage of this method lies in the fact that the controller is intelligent enough to (1) choose the centre values of the output fuzzy set on its own, though the controller is provided with starting centre values. And (2), with this method there is no need to give initial PI values, thus making the whole control process automatic.

### 6.4.2 Adjustment of Weights around fixed values

In this case, weights are tuned around fixed weight values as given by equation (6.19). The constant weight values correspond to centers of the output fuzzy set taken from a simple fuzzy controller. In other words, this method provides fine tuning to the fuzzy rule base. In this method, some initial gain values are required to be provided to the PI controller.

$$\Delta w_i(t + 1) = w_i + \Delta w_i(t)$$

(6.19)
Here, $w_i$ represents the fixed centre value of the $i^{th}$ output fuzzy set, $\Delta w_i(t + 1)$ gives the updated value and $\Delta w_i(t)$ signifies the value by which the weight or centre of the $i^{th}$ node is updated at time $t$.

For the proposed controller, the method of continuous adjustment of weights is chosen as it adds more intelligence to the controller. Simulation results for the NF controller with adjustment of weights around fixed values are also provided for comparison purposes.

### 6.5 NF + PI Controller

As shown in Figure 6.4, the output of the NF controller is connected to the gains of the conventional PI controller. NF controller adapts these gains according to the following equations:

\[
K_p = \Delta K_p \tag{6.20}
\]

\[
K_i = \Delta K_i \tag{6.21}
\]

Where, $\Delta K_p$, $\Delta K_i$ are the outputs of the NF controller. Equations (6.20) and (6.21) are used when the method of continuous weight adjustment is used. As seen from these equations, the output of the NF controller is used directly to adjust the PI gains without
the need of any initial gain values and even a scaling factor. While on the other hand, equation (6.22) and (6.23) are used when weight adjustment is done around some initial values obtained from fuzzy rule base as summarized using Table 6.1. This case requires initial PI gain values.

\[
K_p = K_{p0} + k_p \Delta K_p \quad (6.22)
\]

\[
K_i = K_{i0} + k_i \Delta K_i \quad (6.23)
\]

Where \(K_{p0}\) and \(K_{i0}\) represent initial proportional and integral gains; \(\Delta K_p, \Delta K_i\) gives outputs of the NF controller and \(k_p, k_i\) symbolize scaling factor of the controller.

**TABLE 6.1**

<table>
<thead>
<tr>
<th>e/\Delta e</th>
<th>NB</th>
<th>ZE</th>
<th>PB</th>
</tr>
</thead>
<tbody>
<tr>
<td>NB</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td>ZE</td>
<td>PS</td>
<td>ZE</td>
<td>PS</td>
</tr>
<tr>
<td>PB</td>
<td>PB</td>
<td>PS</td>
<td>PB</td>
</tr>
</tbody>
</table>
6.6 Online Adaptation of Learning Rate and Momentum Using FL Approach

Learning rate ($\eta$) and momentum ($\mu$) form the two most essential parameters in the design of the NF controller. Therefore, for the optimum performance of the controller the correct choice of these parameters is important. From the analysis of the NF controller it is observed that response time of the controller varies with the variation of $\eta$ and $\mu$.

Higher values of learning rate and momentum are desired during the transient states while during steady state it is better to have lower values of $\eta$ and $\mu$ to avoid
higher overshoot. An attempt is made to achieve this objective by using FL approach for the online adaptation of learning rate and momentum. With the successful implementation FL control for deciding the values of learning rate and momentum following benefits are expected:

(1) Significant improvement in the performance of the NF controller for a HVDC system.

(2) No need of using trial and error method for finding the optimum values of these parameters \((\eta, \mu)\) which is a time consuming process.

The following section discusses the design of the FL controller for learning rate and momentum. The simulation results for this approach along with a performance comparison with NF controller with fixed values of learning rate and momentum is provided in the section 6.7.

### 6.6.1 Design of FL Controller for Learning Rate and Momentum

Figure 6.5 shows FL controller for learning rate and momentum as built in EMTP-RV. FL controller consists of four basic parts i.e. fuzzification, fuzzy rule base, inference engine and defuzzification. Since FL approach has already been discussed in detail in chapter 3, therefore, a brief description only in the context of controller design is provided here. The design of FL controller for both learning rate and momentum is similar with the only difference in fuzzy rule base.
Figure 6.5—FL Controller of Learning Rate and Momentum as built in EMTP-RV
6.6.1.1 Fuzzification

The current error and rate of change of this error are taken as inputs to the fuzzification block. Three triangular MFs over a Universe of Discourse of [1,-1] are used for both the inputs while singleton fuzzy sets (MFs) are used for the output.

6.6.1.2 Fuzzy Rule Base

The rule base gives appropriate control action corresponding to the inputs. Corresponding to two inputs and three MFs for each input; fuzzy rule base comprises of nine rules. Fuzzy rule base for learning rate and momentum is given by Tables 6.2 and 6.3 respectively.

6.6.1.3 Fuzzy Inference Engine

The Larsen implication operator (product) is used to calculate the output of each individual rule in the fuzzy rule base.

<table>
<thead>
<tr>
<th>TABLE 6.2</th>
<th>Rule Base for Learning Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>e/Δe</td>
<td>NB</td>
</tr>
<tr>
<td>NB</td>
<td>PB</td>
</tr>
<tr>
<td>ZE</td>
<td>PB</td>
</tr>
<tr>
<td>PB</td>
<td>PS</td>
</tr>
</tbody>
</table>
### TABLE 6.3
Rule Base for Momentum

<table>
<thead>
<tr>
<th>e/Δe</th>
<th>NB</th>
<th>ZE</th>
<th>PB</th>
</tr>
</thead>
<tbody>
<tr>
<td>NB</td>
<td>PB</td>
<td>PS</td>
<td>PB</td>
</tr>
<tr>
<td>ZE</td>
<td>PB</td>
<td>PS</td>
<td>PB</td>
</tr>
<tr>
<td>PB</td>
<td>PS</td>
<td>PB</td>
<td>PB</td>
</tr>
</tbody>
</table>

#### 6.6.1.4 Defuzzification

Centre Average Defuzzifier is used for the defuzzification of the output.

#### 6.6.2 NF Controller with Fuzzy Modification

Figure 6.6 shows block diagram of FL modified NF controller. The output of the FL controller for both learning rate and momentum is applied directly to the NF controller. Hence, the values learning rate and momentum values are updated with the change in system conditions. The output of the NF controller is used to update the PI gains of conventional PI controller as discussed in previous sections.
6.7 Simulation & Results

To test the robustness of the proposed NF controller, HVDC system is subjected to test sequences such as step change in current order and three phase AC fault at the rectifier and the performance comparison have been made for the following cases:

- **Case 1**: Performance comparison between the NF controller with RBF architecture (NF with Gaussian MF), NF controller with CMAC architecture (NF with Triangular MF) and conventional PI controller.

- **Case 2**: Performance comparison between NF controller with continuous adjustment of weights and NF controller with tuning of weights around fixed
values. For this comparison, NF controller with Gaussian MF is chosen.

- **Case 3**: In this case, a performance comparison of NF controller with fixed values of learning rate and momentum with FL modified NF controller i.e. with varying values of these parameters is made.

### 6.7.1 Case 1

In this case, a performance comparison between NF controller with RBF architecture (NF with Gaussian MF), NF controller with CMAC architecture (NF with Triangular MF) and conventional PI controller has been made. This is done by putting the HVDC system to step changes of 30% and 50% in the current order and a 100 ms three phase fault at the rectifier.

The method of continuous adjustment of weights has been used for both the configuration of NF controller with fixed value of learning rate ($\eta$) and momentum ($\mu$).

### 6.7.1.1 Step Changes in Current Order (30% and 50%)

To test the controllability and speed of response of the proposed controller, step changes of 30% and 50% are applied to the current reference.
For 30% step change in current order (Figure 6.7), all the three controllers i.e. NF (Gaussian MF), NF (Triangular MF) and PI give satisfactory performance with proposed controllers having lower overshoot and lower settling time, as indicated in Table 6.4.

For large disturbances (50% step change), conventional PI controller suffers a commutation failure and fails to give satisfactory performance. On the other hand, NF controllers recover well from the large disturbance (Figure 6.8) with low overshoot and settling time, as shown in Table 6.5.

Overall, from this comparison it is concluded that NF controller with triangular (CMAC) or gaussian (RBF) MFs give similar performance which may be attributed to the fact that both the MFs have similar width and as analyzed in chapter 4, MFs with different shapes but similar width does not have a significant effect on the performance of the FL controller.

**TABLE 6.4**
30% Step Change in Current Order

<table>
<thead>
<tr>
<th>Controller</th>
<th>$T_r$ (ms)</th>
<th>%OS</th>
<th>$T_s$ (ms)</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>NF (Gaussian MF)</td>
<td>13</td>
<td>11.9</td>
<td>60.8</td>
<td>SR</td>
</tr>
<tr>
<td>NF (Triangular MF)</td>
<td>13</td>
<td>11.8</td>
<td>60.3</td>
<td>SR</td>
</tr>
<tr>
<td>PI</td>
<td>13</td>
<td>12.9</td>
<td>76.3</td>
<td>SR</td>
</tr>
</tbody>
</table>

*$T_r$ = Rise Time; OS = Overshoot; $T_s$ = Settling Time; SR = Smooth Recovery
Figure 6.7—PI, NF (Gaussian MF) & NF (Triangular MF) response to 30% step change respectively
Figure 6.8— PI, NF (Gaussian) & NF (Triangular) response to 50% step change respectively
### Table 6.5
50% Step Change in Current Order

<table>
<thead>
<tr>
<th>Controller</th>
<th>$T_r$ (ms)</th>
<th>$%OS$</th>
<th>$T_s$ (ms)</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>NF (Gaussian MF)</td>
<td>12</td>
<td>14.6</td>
<td>70.47</td>
<td>No CF, SR</td>
</tr>
<tr>
<td>NF (Triangular MF)</td>
<td>12</td>
<td>14.5</td>
<td>67.65</td>
<td>No CF, SR</td>
</tr>
<tr>
<td>PI</td>
<td>32.8</td>
<td>34.64</td>
<td>H</td>
<td>CF &amp; Recovery with Harmonics</td>
</tr>
</tbody>
</table>

*CF = Commutation Failure; OS = Overshoot; SR = Smooth Recovery

#### 6.7.1.2 Three Phase Fault at Rectifier (100 ms)

During a 3-phase fault there is a collapse of DC link with no current/power flowing through the system. Under such circumstances, the efficacy of the controller is evaluated based on its ability to recover as soon as the fault is cleared.

A 5-cycle, 3-phase AC fault is created at the rectifier end. During the fault, Voltage Dependent Current Limit (VDCL) reference falls to 0.3 pu and ramps back up to 1 pu when the fault is cleared. From the simulation results (Figure 6.9), it is observed that the proposed NF controller with any architecture i.e. RBF or CMAC follows the VDCL reference much better than the conventional PI controller demonstrating faster response and stability of the proposed controller. If observed carefully, there is slight difference between the performance of the NF controller with Gaussian MF and NF controller with Triangular MF; NF controller with Gaussian MF has a smoother response compared to NF controller with Triangular MF as observed from the variation in the proportional gain (Figure 6.9) for both the configurations of NF controller.
Figure 6.9—PI, NF (Triangular) & NF (Gaussian) response to 5-Cycle 3-Phase Fault respectively

6.7.2 Case 2

In this case, a performance comparison between NF controller with continuous adjustment of weights and NF controller with tuning of weights around fixed values has been made. For this, HVDC system is put to the test sequences such as step changes in current order (30% and 50%) and a 100 ms three phase fault at the rectifier.
For both the methods, FL approach for the online adaptation of learning rate ($\eta$) and momentum ($\mu$) has been used.

### 6.7.2.1 Step Changes in Current Order (30% and 50%)

For the 30% and 50% step change in current order, both the controllers i.e. NF controller (with continuous adjustment of weights) and NF controller (with tuning of weights around fixed values) gave satisfactory and similar performance in terms of rise time ($T_r$), % overshoot ($\% OS$) and settling time ($T_s$) as summarized in Table 6.6 and 6.7 respectively and shown in Figures 6.10-6.13.

If observed carefully, it is seen that NF controller (with continuous adjustment of weights) has lower steady state error (SSE) almost zero compared to NF controller with (with tuning of weights around fixed values), though the SSE for both the controller is within the allowable limit of 5%. This observation is more prominent for a large disturbance of 50% in the current order.
**Figure 6.10**—NF (Continuous Adjustment of Weights) response to 30% step change

**Figure 6.11**—NF (Tuning of Weights around fixed values) response to 30% step change
Figure 6.12—NF (Continuous Adjustment of Weights) response to 50% step change

Figure 6.13—NF (Tuning of Weights around fixed values) response to 50% step change
### TABLE 6.6
30% Step Change in Current Order

<table>
<thead>
<tr>
<th>Controller</th>
<th>$T_r$ (ms)</th>
<th>%OS</th>
<th>$T_s$ (ms)</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>NF (Continuous Adjustment of Weights)</td>
<td>13</td>
<td>11.9</td>
<td>60.8</td>
<td>SR</td>
</tr>
<tr>
<td>NF (Tuning of Weights around fixed values)</td>
<td>13.12</td>
<td>9.09</td>
<td>70.9</td>
<td>SR</td>
</tr>
</tbody>
</table>

*T_r = Rise Time; OS = Overshoot; $T_s$ = Settling Time; SR = Smooth Recovery

### TABLE 6.7
50% Step Change in Current Order

<table>
<thead>
<tr>
<th>Controller</th>
<th>$T_r$ (ms)</th>
<th>%OS</th>
<th>$T_s$ (ms)</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>NF (Continuous Adjustment of Weights)</td>
<td>14</td>
<td>13.04</td>
<td>64</td>
<td>SR</td>
</tr>
<tr>
<td>NF (Tuning of Weights around fixed values)</td>
<td>14</td>
<td>13.79</td>
<td>70.6</td>
<td>SR</td>
</tr>
</tbody>
</table>

*CF = Commutation Failure; OS = Overshoot; SR = Smooth Recovery

#### 6.7.2.2 Three Phase Fault at Rectifier (100 ms)

A 5-cycle, 3-phase AC fault is created at the rectifier end. When the fault is cleared it is observed that NF controller (with continuous adjustment of weights) follows the reference value quite well (Figure 6.14) while the NF controller (Tuning of Weights around fixed values) recover slowly with a high SSE (Figure 6.15) which takes some time to be reduced to values within the tolerance limit. For NF controller (with continuous adjustment of weights) clear updation in the value of proportional gain can be seen in the Figure 6.14 which is the reason for the faster response of the controller.
Figure 6.14—NF (Continuous Adjustment of Weights) response to 100 ms 3-phase fault

Figure 6.15—NF (Tuning of Weights around fixed values) response to 100 ms 3-phase fault
6.7.3 Case 3

In this case, the performance of the NF controller with fixed values of learning rate and momentum is compared to the NF controller with varying values of these parameters. As in Case 1 NF controller with fixed values of learning rate and momentum is used while in Case 2, FL approach for the online adaptation of learning rate and momentum has been used therefore, data from both the cases can be used to make a performance comparison. The results taken from both these cases correspond to the NF controller with continuous adjustment of weights.

6.7.3.1 Step change in Current Order (30% and 50%)

As seen from Table 6.8 and 6.9, for 50% step change the NF controller with varying learning rate and momentum has a slightly better performance than the NF controller with fixed values of learning rate and momentum while for 30% step change no difference is seen in the performance of both the controllers.

<table>
<thead>
<tr>
<th>Controller</th>
<th>$T_r$(ms)</th>
<th>%OS</th>
<th>$T_s$(ms)</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>NF (Fixed Values of $\eta$ and $\mu$)</td>
<td>13</td>
<td>11.9</td>
<td>60.8</td>
<td>SR</td>
</tr>
<tr>
<td>NF (Varying Values of $\eta$ and $\mu$)</td>
<td>13</td>
<td>11.9</td>
<td>60.8</td>
<td>SR</td>
</tr>
</tbody>
</table>

* $T_r$ = Rise Time; OS = Overshoot; $T_s$ = Settling Time; SR = Smooth Recovery
The results are not according to expectations as significant improvement was expected with the use of FL approach to decide the value of learning rate and momentum.

<table>
<thead>
<tr>
<th>Controller</th>
<th>$T_r$ (ms)</th>
<th>%OS</th>
<th>$T_s$ (ms)</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>NF (Fixed Values of $\eta$ and $\mu$)</td>
<td>12</td>
<td>14.6</td>
<td>70.47</td>
<td>SR</td>
</tr>
<tr>
<td>NF (Varying Values of $\eta$ and $\mu$)</td>
<td>14</td>
<td>13.04</td>
<td>64</td>
<td>SR</td>
</tr>
</tbody>
</table>

*CF = Commutation Failure; OS = Overshoot; SR = Smooth Recovery

6.8 Summary

In this chapter, FL and NNs are combined together to propose a hybrid NF controller for a HVDC system. A feedforward NN architecture has been used. In addition to this design of FL controller to tune the parameters of NF controller has been discussed. Furthermore, performance comparison for various configurations of NF controller is made. Simulation results clearly show the successful implementation of the NF controller in EMTP-RV simulation package.
CHAPTER 7

CONCLUSION AND FURTHER WORK

7.1 Conclusions

This thesis deals with the design and optimization of a FL based current controller for a HVDC plant. First, an adaptive Fuzzy PI controller is designed to adapt to the proportional (P) and Integral (I) gains of a conventional PI controller for the rectifier current control of the HVDC system. Then, extensive simulation work has been carried out for the optimization of the two key parameters in the design of the FL controller i.e. MFs and fuzzy rule base. This is done by:

1. Studying the effect of various MF shapes, widths and distribution on the performance of a FL controlled HVDC system under different system conditions.
2. Combining NNs and FL together, a novel neuro-fuzzy controller has been proposed to tune the rule base of the FL based PI controller.

7.1.1 Influence of MFs

The FL based PI controller is tested with eighteen different choices of MFs to find
out up to what extent shape, width and distribution of MFs affect the performance of the
HVDC system and to provide designers with more choice other than just basic Triangular
MFs. From the results, the following conclusions can be drawn:

- FL-based PI controller has a superior performance than the conventional PI controller for any choice of MF,
- The shape of the MFs slightly affects the performance, with nonlinear MFs (Gaussian) being better than linear MFs,
- The width of the MFs has a significant effect in terms of rise time ($t_r$), settling time ($t_s$) and overshoot,
- Polynomial Distribution has a slightly worse or similar performance to linear Distribution. Therefore, Linear Distribution of MFs is recommended to be used for the control of HVDC system.

Overall, based on this study, nonlinear MFs such as Gaussian, Two-Sided Gaussian and Bell with medium or large widths are recommended for a FL based controller for a HVDC system as nonlinear MFs offers greater fuzziness than linear MFs.

7.1.2 NF based PI Controller

FL and NNs are combined together to propose a hybrid NF controller for a HVDC system. Simulation results clearly show the successful implementation of the NF controller in EMTP-RV simulation package. Following observations can be made from the results:

- NF controller effectively updates the Rule Base with changing system conditions,
• NF controller with either choice of architecture i.e. RBF or CMAC has a better performance than conventional PI controller,

• Both NF (Gaussian MF) and NF (Triangular MF) gave almost similar performance in terms of rise time ($t_r$), settling time ($t_s$) and overshoot. This may be due to the fact that both the MFs used belong to the medium category and as concluded before using MFs of different shapes but similar width does not make much of a difference in the controller’s performance,

• NF controller is capable of tuning PI gain values for different system conditions without the need for any initial values,

• NF controller has a slow initial response as with no initial gain values, it takes some iteration to reach to correct gain values,

• The use FL approach to find out the appropriate values of momentum and learning rates for a NF controller slightly affects the performance of the controller.

This work shows the potential of the NF control scheme for a HVDC system. As seen from the results, NF controller provides a more intelligent solution to the control of HVDC systems as compared to other methods such as FL control and other adaptive and optimal control methods.
7.2 Recommendations for Further Work

Based on the work done in this thesis, the following recommendations are made for further work in this area:

- From the investigation of MFs of various shapes, width and distribution; it is found that the width of the MF is a key element in the tuning of the MFs. Therefore, further investigation can be made towards automatic tuning of the width of the MF with changing system conditions.

- With successful implementation of the NF controller for the rectifier current control of the HVDC system, a similar controller can also be used for the inverter side of the system.

- The ability of the proposed NF controller to update the fuzzy rule base online can be extended to the tuning of the fuzzy MFs.

- The proposed NF controller showed better results, however extensive validations needs to be carried out under a real time simulation environment.
REFERENCES


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APPENDIX A: HVDC System Data

AC Side

Source Voltage: 230 kV

Source frequency: 50 Hz

Source Impedance: R = 0.25 Ω; L = 45 mH

AC Filter Data

<table>
<thead>
<tr>
<th>Harmonics</th>
<th>R (Ω)</th>
<th>L (mH)</th>
<th>C (µF)</th>
<th>Mvars</th>
</tr>
</thead>
<tbody>
<tr>
<td>11th</td>
<td>0.63</td>
<td>27.83</td>
<td>3.009</td>
<td>60</td>
</tr>
<tr>
<td>13th</td>
<td>0.63</td>
<td>19.52</td>
<td>3.009</td>
<td>60</td>
</tr>
<tr>
<td>High Pass</td>
<td>82.6</td>
<td>3.84</td>
<td>4.57</td>
<td>91.2</td>
</tr>
</tbody>
</table>

Transformer

Yg-Y : 230:205.45 kV; 500 MVA

Yg-∆ : 230:205.45 kV; 500 MVA

DC Side

R = 2.5 Ω; L = 350 mH

V_d = 440 kV; I_d = 1600 A; P_d = 704 MW

DC Filter (12th Harmonic) = ( R = 1Ω; L = 0.2814 mH; C = 1 µF)
Figure B— Test HVDC system model in EMTP-RV
Figure C—Schematic of FL controller as in EMTP-RV
APPENDIX D: NF Controller in EMTP-RV

NEURO-FUZZY (NF) CONTROLLER IN EMTP-RV

Figure D — Schematic of NF controller as in EMTP-RV
List of Publications from this Work

(1) M. Multani, J. Ren and V.K. Sood (2010); “Fuzzy Logic (FL) Controlled HVDC System-Influence of Shape, Width & Distribution of Membership Functions (MFs),” proceedings of 23rd Canadian Conference on Electrical and Computer Engineering, IEEE CCECE ’10, 2-5 May, 2010, Calgary, Canada