Incremental Fuzzy PI Control of a HVDC Plant

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ABSTRACT

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High Voltage Direct Current (HVDC) transmission systems traditionally use PI controllers with fixed gains. These controllers operate satisfactorily within a small operating range because of the non-linearity and uncertainty of the plant. However, when AC systems are weak, the HVDC systems are prone to repetitive commutation failures under disturbances, which may lead to the instability and collapse of the DC link.

This thesis is a contribution to the study of these problems. In order to make the HVDC systems have optimal control over a wider operating range, an Incremental Fuzzy Gain Scheduling Proportional and Integral Controller (IFGSPIC) is proposed for the current control of the rectifier. For this study using the EMTP RV simulation package, a typical HVDC system connected to a weak AC system is modeled with the detailed representation of the converter, converter transformer and AC/DC filters etc. The DC current error and its derivative are taken as two parameters necessary to adapt the proportional (P) and integral (I) gains of the current controller based on fuzzy reasoning.

Two different fuzzy rule bases are designed to tune the PI gains independently. The fuzzy control rules and analysis of IFGSPIC are presented. A Larsen reference engine, center average defuzzification and most natural and unbiased membership functions (MFs) (i.e. symmetrical triangles and trapezoids with equal base and 50% overlap with neighboring membership functions) are used. This simplifies the controller design and reduces computation time under the EMTP RV simulation environment.

The IFGSPIC is designed to combine the advantages of a FL controller and a conventional PI controller to improve the transient and steady state performance. During transient state, the PI gains are adapted by the IFGSPIC to damp out the amplitude of undesirable oscillations around the set point and reduce settling time. During the steady state, the controller is automatically switched back to the conventional PI controller to maintain the control stability and accuracy. Performance evaluation under AC fault and set-point step change is studied. Results from the various tests show that the proposed controller can achieve satisfactory control results in a wide operating range for the HVDC plant.

To my late father ZHAOLIN QI

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Finally, I am heartily grateful to my parents for their endless love, support and encouragement throughout my life.

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LIST OF PRINCIPAL SYMBOLS

V_d	DC line voltage
I_d	DC line current
P_d	DC power
P	Proportional control
I	Integral control
$e(k)$	Error
$\Delta e(k)$	Change of error
$u(k)$	Control signal
$\Delta u(k)$	Incremental change of control signal
r	Input
y	Output
$\mu(x)$	Membership function
Δu_N	FLC output
G_e	Scaling factor of error
$G_{\Delta e}$	Scaling factor of change of error
$G_{\Delta u}$	Scaling factor of FLC output

K_p	Proportional gain
K_i	Integral gain
K_{p0}	Initial proportional gain
K_{i0}	Initial integral gain
k_p	Proportional scaling factor
k_i	Integral scaling factor
CV_p	Proportional fuzzy-control matrix
CV_i	Integral fuzzy-control matrix
$u_c(t)$	Conventional PI control output
t_r	Rise time
%OS	Percent maximum overshoot
t_s	Five percent settling time
ISE	Integral of the squared error
IAE	Integral of the absolute error
Iref	Reference current
A, B, C	Arbitrary fuzzy sets
$\mu_A(x)$	Membership value of fuzzy set *A* at support point *x*
Min or $\wedge$	Minimum
Max or $\vee$	Maximum
T	T-norms
S	S-norms

I or A→B	Implication
Agg	Aggregation
$\in$	Belong to
$\forall$	For all
$\circ$	Composition
If-then	Linguistic rule
and	Linguistic conjunction
$z_i^{'}$	Center of the i'th fuzzy set
K	Proportional gain
Ti	Integral time constant
Td	Derivative time constant
Kr	Critical gain at the critical oscillation point
Tr	Period at the critical oscillation point

Chapter 1

General Background and Research Goals

1.1 Introduction

Modern High Voltage Direct Current (HVDC) technology was first used in the under-sea cable interconnections of Gotland in 1954. Since then, the increasing use of HVDC transmission systems has made it a competitive alternative for AC transmission systems. Although HVDC transmission systems have many advantages over AC transmission systems, such systems are used primarily in specialized circumstances due to their high initial costs and inherent difficulties to operate with weak AC systems [1].

Traditionally, HVDC transmission systems use PI controllers with fixed PI gains. Such controllers work well for perturbations within a small operating range. However, when AC systems are weak, the HVDC transmission systems are prone to repetitive commutation failures under disturbances, which may lead to the instability and collapse of the DC link.

To overcome above mentioned problems, research into alternative and advanced controllers in the area of HVDC transmission systems control is being carried out. In [2], it is pointed out that the absence of insight into a system's performance with large disturbances may make some modern control methods, such as adaptive control, robust coordinated control, and Kalman filtering approach, ineffective and even degrade the performance because these controllers need an accurate plant model and the algorithms used are complicated.

Recently, extensive research in the area of intelligent control systems has drawn more attention for non-linear dynamical systems due to their ability to mimic human beings [3]. Among the intelligent systems, Neural Networks (NNs) have been applied due to their ability to acquire information and to learn through training [4]. Fuzzy Logic (FL) has been used to handle uncertainties for large non-linear systems [5]. The fact that intelligent systems do not require an accurate mathematical model of the system makes them attractive for their application to large non-linear systems such as HVDC transmission systems.

1.2 Research Motivation

The proper control method of HVDC transmission systems is the key factor to keep the power systems working well and to ensure power transmission quality.

This thesis is concerned with controlling the HVDC transmission system's voltage and current under small and large disturbances. The objective of this work is to study and employ intelligent systems in HVDC transmission systems to cope with different operation conditions. The insensitivity of intelligent controllers to the mathematical model of the power systems enables us to improve dynamic performance of HVDC transmission systems especially when connected with weak AC systems. Hence, using intelligent systems in HVDC transmission systems control does validate its usefulness and encourage engineers to use this technique in other power systems applications.

1.3 Problem Definition

The operation and control of HVDC transmission systems poses a challenge for the designers to choose the proper control strategy under various operating conditions. There are several problems related to the control of HVDC transmission systems that should be emphasized here:

- HVDC transmission systems are highly non-linear (i.e. due to transformer saturation and converter's switches turning on and off, etc). One problem with fixed-gain PI type controllers is that, in essentially non-linear systems, their performance can only be optimal at one operating point.
- The accurate dynamic mathematical model of the system is difficult to obtain because the system is complex and varies with time. This may be especially true when connected with weak AC systems. This leads to difficulties when used with control methods which need an accurate mathematical model.
- The use of AC/DC filters in the system can often cause resonance with the behavior of the power system. The generation of harmonics by the converters can interact with

the controllers, which need to have sufficient damping ability.

- The control mode transitions which lead to abrupt change of parameters may cause system instability.
- When the strength of the AC systems connected to the terminals of a DC link is weak, the operation and control of an HVDC transmission system is often difficult [6]. Very often in such systems, under certain circumstances due to model uncertainties, and shifts in operating points, traditional PI controllers with fixed values of proportional and integral gains may lead to instability and collapse of the DC link owing to repetitive commutation failures.

The work presented here is to overcome these problems using a properly selected control method.

1.4 Literature Review

Recently, extensive research in the area of intelligent systems (FL and NN) has been directed towards power systems' applications. Most of these applications are in AC systems and only a few publications exist in the application of intelligent controllers for HVDC systems [2, 7 - 12].

In [7], a NN-based controller makes use of a simple feedforward NN architecture with one hidden layer and Back Propagation (BP) training algorithm to control the current of the rectifier of an HVDC transmission system under typical system perturbations and faults. The experimental results show that NN controller can overcome repetitive commutation failures, but the response of NN controllers is slower than the PI controller.

In [8], the authors also used a feedforward NN as a controller for the same HVDC plant. Since the desired control (alpha order) is not directly available, an error reinforcement learning algorithm for weight training and activation function's slope adaptation is used to determine the target controller output from the HVDC plant response. Compared to a PI controller, the proposed controller presents its advantages in overcoming commutation failure and fast response under large signal disturbances. But for small signal disturbances, the response is slower than a PI controller. One drawback of this publication was that the model of the HVDC system employed is a linear model, which lost generality because HVDC transmission systems are inherently non-linear systems.

In [9], a neuro-fuzzy VDCL unit is proposed to overcome the tendency to commutation failures when an HVDC converter is used with a weak ac system. Experiments show the proposed methods can avoid hitting alpha minimum limit and damping oscillations. The shortcoming of this method is that too many neurons in the NN will require much computation time, which would degrade the fast response. However, with the availability of faster computers, this problem is no longer considered to be relevant.

The global approximation ability of fuzzy logic controllers has attracted growing attention and is a topic of great interest to large non-linear systems such as HVDC transmission systems. Fuzzy logic controllers have proven themselves successful in controlling low-order linear systems and small non-linear plants. For high-order linear systems and large non-linear systems, fuzzy logic controllers seem to work even worse than conventional PI controllers. Therefore, combining the advantages of a fuzzy logic controller with a conventional PI controller and using fuzzy logic to do on-line scheduling of the PI gains according to the operational condition appears to offer another alternative way [2, 10 - 12].

In [10], the authors present a fuzzy logic based approach for the on-line tuning of the control parameters. Two fuzzy logic controllers are investigated for a point to point HVDC link connected to weak AC systems. One controller uses an error signal as the input for fuzzy reasoning. The other controller is based on a Lyapunov energy function. Both controllers had a better performance than a conventional PI controller.

In [11], to compare the performance with the fuzzy controller, variable structure and self-tuning controllers are used in the control loop of the rectifier's current regulator. To employ variable structure and self-tuning controllers, a simplified HVDC plant with an approximate mathematical model instead of the real HVDC plant is used. The experimental results from this simplified plant show that a variable structure controller provides robustness and insensitivity to parameter variation. Furthermore, a self-tuning controller provides an excellent tracking of the system output and is able to handle uncertainties. But the fuzzy controller does not require an accurate mathematical model of the system and, using a minimum number of rules, it can produce the same or even better performance compared to variable structure and adaptive controllers.

In [12], the authors focus on using fuzzy logic to control the transition from one control mode to another in order to avoid abrupt change of control modes. The abrupt change of control modes may cause a sudden change of the gains, time constants and controlling error. Gradual transition in the selecting control mode process is made by fuzzy reasoning, which improved the system transient response. Experimental results show that this control method provides improved immunity to commutation failure.

In [2], the paper also presents an energy function based on a fuzzy logic approach for scheduling the PI gains of a HVDC link connected to weak AC systems. Since the fuzzy rules are derived from a Lyapunov stabilization criterion, the approach should be inherently stable. Two simple rule bases with respect to proportional and integral gains are deduced according to the operational condition.

In [37], the authors address gain scheduling controllers using linearization-based scheduling and linear parameter-varying (LPV) approaches. They present innovative gain scheduling approaches in theoretical research and practical applications.

While some interesting techniques and results have been presented in the above mentioned publications, there still exists room suggest other techniques to improve performance. Using the different rule bases according to proportional and integral characteristics for tuning PI gains and deriving more rules for each rule base, it is hoped that fuzzy logic controllers will improve the control performance.

1.5 Research Objectives and Contributions

The objectives of this research are to utilize intelligent system techniques for development of intelligent controllers for HVDC transmission systems under various disturbances. Specifically, the goal is to improve transient response performance to stabilize the system, which improves power transmission quality through regulating the current of the rectifier in HVDC converter stations. In order to achieve these objectives, fuzzy logic controllers are studied to perform the above task. The fuzzy logic controllers considered here are general fuzzy PI-like controller and incremental fuzzy gain scheduling PI controller. This thesis presents the technique of applying fuzzy logic controllers to control HVDC transmission systems connected with weak AC systems. To improve system's performance, analysis of fuzzy logic controllers is provided and new fuzzy control rules are proposed with respect to scheduling proportional and integral gains. A comparative study is conducted on the performance of two fuzzy logic controllers and a conventional PI controller via simulations under the EMTP RV simulation environment. The possibility of using an incremental fuzzy gain scheduling PI controller in the operation and control of HVDC transmission systems under EMTP RV simulation environment was explored for the first time. The objective was to improve performance as compared to the other controllers studied.

1.6 Outline of the Thesis

In Chapter 2, a typical HVDC system is presented. Each building block of the HVDC transmission system is briefly discussed. Control characteristics of the HVDC system are presented. In Chapter 3, an overview of fuzzy logic control is briefly presented. Fuzzy logic and fuzzy control are described. Analysis and design of different fuzzy logic controllers is presented. Chapter 4 presents the implementation and application of fuzzy logic controllers under the EMTP RV simulation environment. A comparative study for different controllers with extensive simulation results are provided in this chapter. In Chapter 5, conclusions of the thesis and recommendations for future work are provided.

Chapter 2

HVDC Transmission Systems

2.1 Introduction

Power is generated in AC form by electrical plants. This power is generally transmitted through three-phase, AC lines to consumer load centers. However, under certain circumstances, power transmission over DC lines becomes more efficient and cost effective. HVDC transmission is advantageous for the following reasons [6, 13]:

- A DC transmission tower has less visual profile than an equivalent AC transmission tower.
- Considering transmission costs, the breakeven distance for HVDC overhead transmission lines usually lies somewhere in a range of 400 to 700 km. Power transmission via an AC cable becomes impractical for distances greater than 50 km but power transmission by DC cable is feasible even for a distance of 600 km.
- DC link enables power transfer between two asynchronous systems.
- Power control through a DC link is fast and precise.
- DC links are reliable and can improve transient stability and dynamic damping of electrical system oscillations.

2.2 HVDC Transmission Systems

There are three types of configuration links possible for HVDC applications: monopolar link, bipolar link, and homopolar link, (Figure 2.1 [1]).

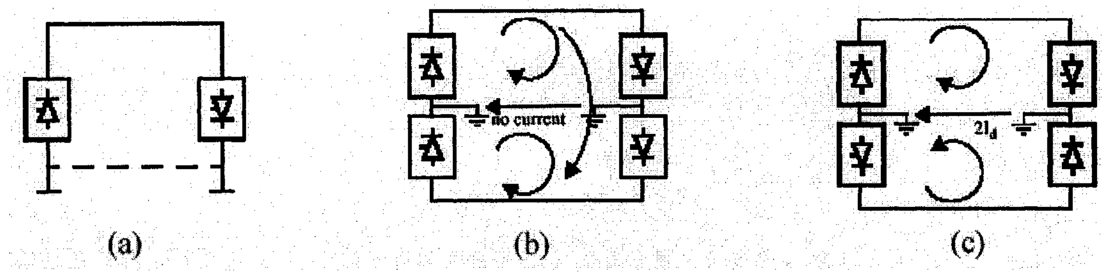

Figure 2.1: DC link configurations (a) monopolar (b) bipolar (c) homopolar

A monopolar link has one conductor, usually of negative polarity, and uses ground or sea return. A bipolar link has both positive and negative conductors. Each terminal has two sets of converters of equal ratings, in series on the DC side. The ground current is zero in this configuration. A homopolar link has two conductors, both having the same polarity (usually negative) and always operating with ground or metallic return. Because of the desirability of operating a DC link without ground currents, bipolar links are most commonly used.

Figure 2.2 shows a typical HVDC converter station [1]. The major components of an HVDC transmission system are the converter stations where power conversion from AC to DC (Rectifier station) and DC to AC (Inverter station) are performed. Power flow over the transmission can be reversed by suitable converter control. Each converter station consists of a positive pole and a negative pole. Each pole consists of two 6-pulse, line-frequency bridge converters connected through a Y-Y and a Δ-Y transformer to yield a 12-pulse converter arrangement. On the AC side of the converter, the filters are required to reduce the current harmonics generated by converter from entering AC system. On the DC side of the converter, the ripple in the DC voltage is prevented from causing excessive ripple in the DC transmission line current by means of smoothing inductors and the DC side filter banks. 12-pulse converter operation has two major advantages. First, it can meet the high voltage requirement of an HVDC system by connecting the two 6-pulse converters in series on the DC side. Second, it can reduce the current harmonics generated on the AC side and the voltage ripple produced on the DC side of the converter through a Y-Y and a Δ-Y transformer.

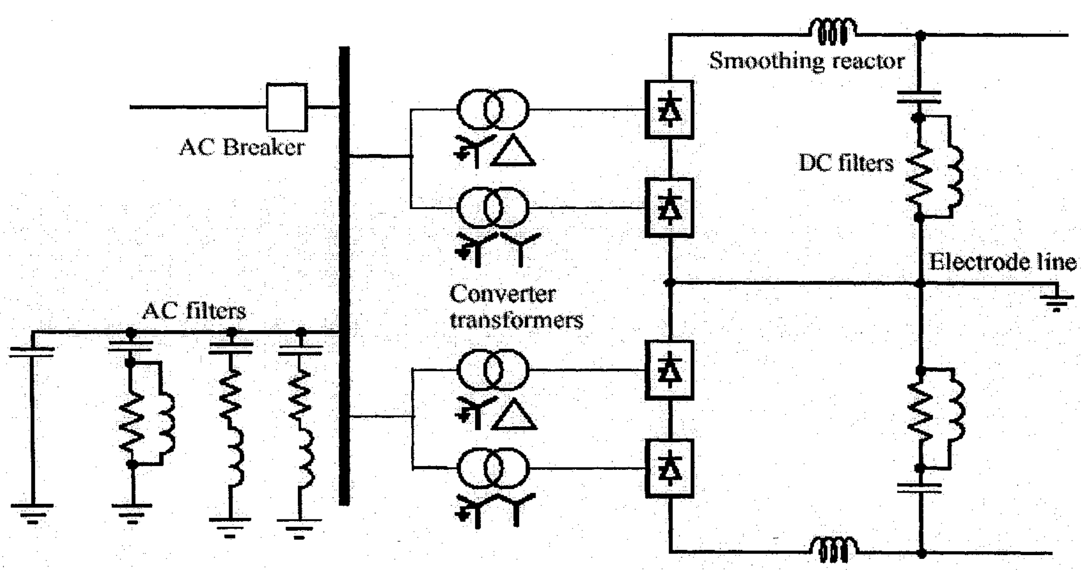

Figure 2.2: A typical HVDC converter station

The model used in this research is a 12-pulse bipolar system, i.e., it consists of positive and negative poles in the converter station. The HVDC system model (Figure 2.3) consists of three sub-systems:

- **Subsystem 1:** This part is the rectifier AC system. It includes a constant voltage, constant frequency source and equivalent impedances. Harmonics filters tuned at 11^{th}, 13^{th}, and high pass frequencies are used in the AC side. A Short Circuit Ratio (SCR) of either 3.8 or 2.3 is used by selecting system parameters to represent either a strong or a weak system respectively. The AC bus bar voltage rating is 230 kV.
- **Subsystem 2:** Two 0.35 H smoothing reactors are used between rectifier and inverter. The nominal DC line voltage Vd at bus G is 440 kV. The DC current Id of the link is 1600 A. The nominal value of DC power Pd is 704 MW.
- **Subsystem 3:** This part is the inverter DC system. It is simplified as a DC sink (440kV) with a diode since the focus of the research is at the rectifier-end and its controller.

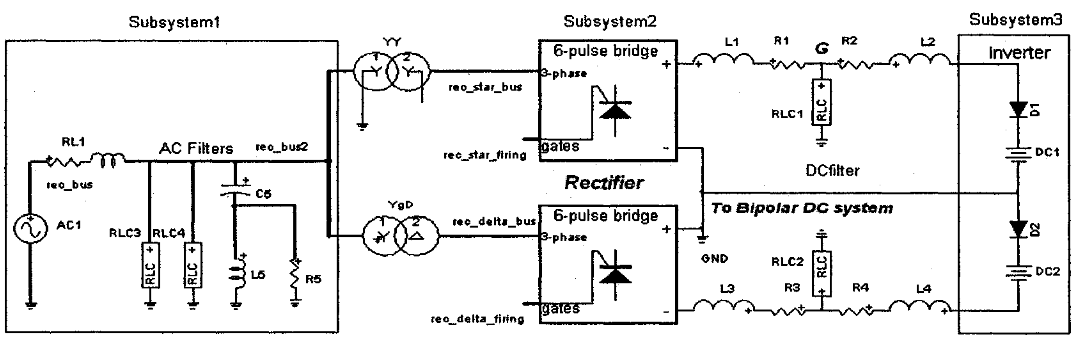

Figure 2.3: HVDC system model

Chapter 3

Fuzzy Logic Controller Design

3.1 Introduction

In the real world, there is inherent impreciseness present in a natural language when phenomena that do not have simple defined boundaries are described. Fuzzy Set & Fuzzy Logic theory provides mathematical tools for carrying out approximate reasoning processes when available information is uncertain, incomplete, imprecise, or vague.

A fuzzy set is a set without a crisp, clearly defined boundary and can contain elements with only a partial degree of membership. Zadeh [14] introduced fuzzy sets in 1965. It is a set with graded membership in the real interval: $\mu_A(x) \in [0, 1]$. In other words, it allows each element of X to belong to the set with a membership degree characterized by a real number in the closed interval [0, 1]. Linguistic variables such as **fast**, **slow** are translated into fuzzy sets; mathematical versions of "**If ... then ...**" rules are formed by combining these fuzzy sets. The use of basic rules of "**If ... then ...**" form are the basic idea behind fuzzy control. In section 3.2, a general FLC design procedure is provided. In section 3.3, a PI like fuzzy controller design is presented. In section 3.4, an Incremental Fuzzy Gain Scheduling PI Controller design is provided.

3.2 Fuzzy Logic for Control

During the past decade, fuzzy logic control, initiated by the pioneering work of Mamdani and Assillian [15] (Steam engine control), which was motivated by Zadeh's paper [16] (A rationale for fuzzy control), has emerged as one of the most active and fruitful areas of research in the application control techniques. Fuzzy logic control is best utilized in complex and ill-defined processes that can be controlled by a skilled human operator without much knowledge of their underlying dynamics. Therefore, the new design techniques are based on more general types of knowledge than differential equation describing the dynamics of the plants.

3.2.1 Fuzzy Inference with Multiple Rules

In a fuzzy logic controller (FLC), the dynamic behavior of a fuzzy system is characterized by a set of linguistic description rules based on an expert's knowledge. The expert knowledge is usually of the form **If** (a set of conditions are satisfied) **then** (a set of consequences can be inferred). Since the antecedents and the consequents of these **If-then** rules are associated with fuzzy concepts (linguistic terms), they are often called **fuzzy conditional statements.**

A **fuzzy control rule** is a fuzzy conditional statement in which the antecedent is a condition in its application domain and the consequent is a control action for the system under control. Basically, fuzzy control rules provide a convenient way for expressing control policy and domain knowledge. Sometimes, several linguistic variables might be involved in the antecedents and the conclusions of these rules. When this is the case, the system will be referred to as a multi-input-multi-output (MIMO) fuzzy system. For example, in the case of two-input-single-output (MISO) fuzzy systems (which is most often used systems in FLC), fuzzy control rules have the form

R1: **If** x is A1 and y is B1 **then** z is C1

also

R2: **If** x is A2 and y is B2 **then** z is C2

also

. . .

also

Rn: **If** x is An and y is Bn **then** z is Cn

where x and y are the process state variables, z is the control variable, Ai, Bi, and Ci are linguistic values of the linguistic variables x, y and z in the universes of discourse U, V, and W, respectively, and an implicit sentence connective *also* links the rules into a rule set or, equivalently, a rule-base.

The FLC can be represented in a form similar to the conventional control law

$$u\ (k) = F\ (e\ (k),\ e(k\text{-}1), \ldots,\ e(k\text{-}\tau),\ u(k\text{-}1), \ldots,\ u(k\text{-}\tau)) \qquad (3.1)$$

where the function F is described by a fuzzy rule-base. However, it does not mean that the FLC is a kind of transfer function or difference equation.

The knowledge-based nature of FLC dictates a limited usage of the past values of the error e and control u because it is rather unreasonable to expect meaningful linguistic statements for $e\ (k\text{-}3)$, $e\ (k\text{-}4)$, . . ., $e\ (k\text{-}\tau)$.

A typical FLC describes the relationship between the changes of the control

$$\Delta u(k) = u(k)\text{-}u(k\text{-}1) \tag{3.2}$$

on the one hand, and the error $e(k)$ and its change

$$\Delta e(k) = e(k)\text{-}e(k\text{-}1) \tag{3.3}$$

on the other hand. Such control law can be formalized as

$$\Delta u(k) = F(e(k),\ \ \Delta(e(k)) \tag{3.4}$$

and is a manifestation of the general FLC expression with $\tau = 1$.

The actual output of the controller $u(k)$ is obtained from the previous value of control $u(k\text{-}1)$ that is updated by $\Delta u(k)$

$$u(k) = u(k\text{-}1) + \Delta u(k) \tag{3.5}$$

This type of controller was suggested originally by Mamdani and Assilian in 1975 [15] and is called the **Mamdani-type** FLC.

Our task is to find a crisp control action z' from the fuzzy rule-base and from the actual crisp inputs x' and y':

R1: **If** x is A1 **and** y is B1 **then** z is C1

also

R2: **If** x is A2 **and** y is B2 **then** z is C2

also

. . .   . . .

also

Rn: **If** x is An **and** y is Bn **then** z is Cn

input   x is x' **and** y is y'

---

output   z'

The inputs of fuzzy rule-based systems are given by fuzzy sets, and therefore, the crisp inputs x' and y' have to be fuzzified. Furthermore, the output of a fuzzy system is always a fuzzy set, and therefore, to get a crisp value, it will have to be defuzzified to get crisp output z'.

Fuzzy logic control systems usually consist of four major parts: **Fuzzification, Fuzzy rule-base, Fuzzy inference engine** and **Defuzzification** (Figure 3.1).

A fuzzification operator has the effect of transforming crisp data into fuzzy sets. In most of the cases, we use fuzzy singletons as fuzzifiers

$$\mu_{A'}(x) = \begin{cases} 1 & if\ x = x' \\ 0 & otherwise \end{cases} \tag{3.6}$$

where x' is a crisp input value from a process (Figure 3.2).

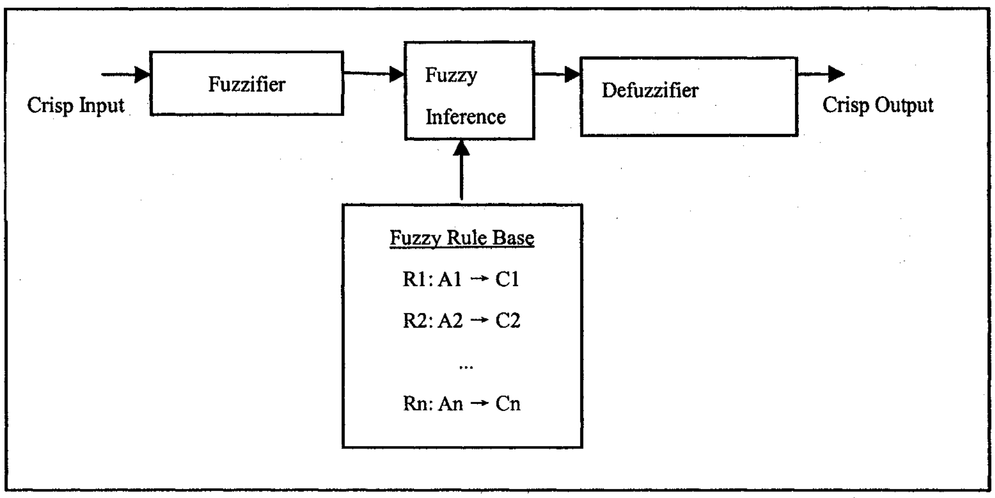

Figure 3.1: Fuzzy logic controller

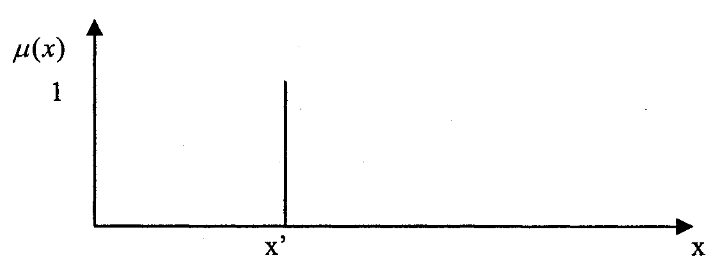

Figure 3.2: Fuzzy singleton as fuzzifier

Suppose now that we have two input variables x and y. A fuzzy control rule

Ri: **If** (x is Ai **and** y is Bi) **then** (z is Ci)

is implemented by a fuzzy implication Ri and is defined as

Ri (u, v, w) = [Ai(u) **and** Bi(v)] →Ci(w)

where the logical connective **and** is implemented by the minimum or product operator, i.e.

[Ai(u) and Bi(v)]→Ci(w) = [Ai(u)×Bi(v)]→Ci(w) = min{Ai(u),Bi(v)}→Ci(w) or

[Ai(u) and Bi(v)]→Ci(w) = [Ai(u)×Bi(v)]→Ci(w) = Ai(u)*Bi(v)→Ci(w)

Of course, we can use any t-norm to model the logical connective *and.*

Fuzzy control rules are combined by using the sentence connective *also.*

Since each fuzzy control rule is represented by a fuzzy relation, the overall behavior of a fuzzy system is characterized by these fuzzy relations.

Symbolically, if we have the collection of rules

R1: **If** x is A1 **and** y is B1 **then** z is C1

also

R2: **If** x is A2 **and** y is B2 **then** z is C2

also

. . . . . .

also

Rn: **If** x is An **and** y is Bn **then** z is Cn

The procedure for obtaining the fuzzy output of such a knowledge base consists of the following three steps:

- Find the firing level of each of the rules.
- Find the output of each of the rules.
- Aggregate the individual rule outputs to obtain the overall system output.

To infer the output z from the given process states x, y and fuzzy relations Ri, the **compositional rule of inference** is applied:

R1: **If** x is A1 **and** y is B1 **then** z is C1

R2: **If** x is A2 **and** y is B2 **then** z is C2

. . . .

Rn: **If** x is An **and** y is Bn **then** z is Cn

fact: x is x' **and** y is y'

---

consequence: z' is C

where the consequence is computed by

consequence = **Agg** ($fact \circ R_1, ..., fact \circ R_n$)*, where **Agg** represents aggregation.

That is,

---

o : composition

$C = \mathbf{Agg}(t(A(x'), B(y')) \circ R_1, ..., t(A(x'), B(y')) \circ R_n)$, where t represents t-norm.

Taking into consideration that

$A(x) = 0$, $x \neq x'$ and $B(y) = 0$, $y \neq y'$,

the computation of the membership function of C is very simple:

$C(w) = \mathbf{Agg}\{t(A1(x'), B1(y')) \rightarrow C1(w), \ldots, t(An(x'), Bn(y')) \rightarrow Cn(w)\}$

for all $w \in W$. This is called **Individual-Rule based Inference** or **Infer and Combine.**

The procedure for obtaining the fuzzy output of such a knowledge base can be formulated as

- The firing level of the i-th rule is determined by t (Ai (x'), Bi (y')).
- The output of the i-th rule is calculated by $C'i(w) := t(Ai(x'), Bi(y')) \rightarrow Ci(w)$ for all $w \in W$.
- The overall system output, C, is obtained from the individual rule outputs C'i by $C(w) = \mathbf{Agg}\{C'1, \ldots, C'n\}$ for all $w \in W$.

3.2.2 Defuzzification Methods

The output of the inference process so far is a fuzzy set, specifying a possibility distribution of control action. In the on-line control, a non-fuzzy (crisp) control action is usually required. Consequently, one must defuzzify the fuzzy control action (output) inferred from the fuzzy control algorithm, namely:

$$z' = \text{defuzzifier}(C),$$

where z' is the non-fuzzy control output and defuzzifier is the defuzzification operator.

The most commonly used defizzifier in fuzzy systems and fuzzy control is the **center of average** method. Because the fuzzy set C is the union or intersection of n fuzzy sets, a good approximation of the center of gravity defuzzifier is the weighted average of the centers of the n fuzzy sets, with the weights equal the heights of the corresponding fuzzy sets, where, the z_i' is the center of the i'th fuzzy set and $C(z_i)$ is its height. This is given by:

$$z' = \frac{\sum_{i=1}^{n} z_i' C(z_i)}{\sum_{i=1}^{n} C(z_i)} \tag{3.7}$$

3.2.3 Design of Fuzzy Logic Controllers Based on Larsen & Mamdani Methods

Here, we only introduce Larsen and Mamdani methods, because they are the most popular methods for FLC.

1. Larsen Implication

Considering the fuzzy logic control systems of the form as following

Ri: **If** x is Ai and y is Bi **then** z is Ci, i = 1, . . . , n

and the fuzzy set Ci is normal with center $z_i^{'}$.

With

- Algebraic product for all t-norm operators and max for all the s-norm operators
- Algebraic product fuzzy conjunction

[Ai (u) and Bi (v)] = Ai (u) Bi (v) or $\mu_{A_i \cap B_i}(x, y) = \mu_{A_i}(x)\mu_{B_i}(y)$ (3.8)

- Product fuzzy implication (Larsen implication)

[Ai(u) and Bi(v)] $\rightarrow$ *C'i(w) =*

Ai(u)Bi(v)Ci(w) or $\mu_{R_i}(x, y, z) = \mu_{A_i}(x)\mu_{B_i}(y)\mu_{C_i}(z)$ (3.9)

Representing each rule by an implication relation

$$\begin{aligned} \mu_{C_i^{'}}(z) &= \sup_{\substack{x \in U \\ y \in V}} t[\mu_{A_i^{'}}(x)\mu_{B_i^{'}}(y),\ \mu_{R_i}(x, y, z)] \\ &= \sup_{\substack{x \in U \\ y \in V}} [\mu_{A_i^{'}}(x)\mu_{B_i^{'}}(y)\mu_{A_i}(x)\mu_{B_i}(y)\mu_{C_i}(z)] \end{aligned} \tag{3.10}$$

- Individual rule-based inference and union combination (s-norm: max)

C(w) = ***Agg****{C'1* $\vee$ . . . $\vee$ *C'n} for all w* $\in$ *W.*

The **Product Inference Engine** is obtained as

$$\mu_C(z) = \max_{i=1}^{n}[\mu_{C_i^{'}}(z)] \tag{3.11}$$

- Singleton fuzzifier

$$\mu_{A_i^{'}}(x) = \begin{cases} 1 & if\ x = x' \\ 0 & otherwise \end{cases} \text{ and } \mu_{B_i^{'}}(x) = \begin{cases} 1 & if\ y = y' \\ 0 & otherwise \end{cases} \tag{3.12}$$

Substituting (3.12) into (3.11), (3.13) is obtained as

$$\mu_C(z) = \max_{i=1}^{n}[\mu_{A_i}(x')\mu_{B_i}(y')\mu_{C_i}(z)] \tag{3.13}$$

- Center average defuzzifier

Since for a given input x' and y', the center of the i'th fuzzy set in (3.13) (that is, the fuzzy set with membership function $\mu_{A_i}(x')\mu_{B_i}(y')\mu_{C_i}(z)$) is the center of Ci, we see that the $z_i^{'}$ in (3.7) is the same in this situation. Additionally, the height of the i'th fuzzy set in (3.13), denoted C(zi) in (3.7), is $\mu_{A_i}(x')\mu_{B_i}(y')\mu_{C_i}(z_i^{'}) = \mu_{A_i}(x')\mu_{B_i}(y')$, (since Ci is normal). Hence, using the center average defuzzifier (3.7) for (3.13), (3.14) is obtained as

$$z' = \frac{\sum_{i=1}^{n} z_i^{'}\mu_{A_i}(x')\mu_{B_i}(y')}{\sum_{i=1}^{n}\mu_{A_i}(x')\mu_{B_i}(y')} \tag{3.14}$$

Let x'=x, y'=y, and z'= f (x, y), thus

$$f(x,y) = \frac{\sum_{i=1}^{n} z_i^{'}\mu_{A_i}(x)\mu_{B_i}(y)}{\sum_{i=1}^{n}\mu_{A_i}(x)\mu_{B_i}(y)} \tag{3.15}$$

Finally, the crisp output z of fuzzy system from crisp inputs x and y is obtained. This is the nonlinear input-output mapping.

2. Mamdani Implication

Considering the fuzzy logic control systems of the form as following

Ri: **If** x is Ai and y is Bi **then** z is Ci, i = 1, . . . , n and the fuzzy set Ci is normal with center $z_i^{'}$.

With

- min for all t-norm operators and max for all the s-norm operators

- Minimum norm fuzzy conjunction

[Ai(u) and Bi(v)_]= min{Ai(u),Bi(v)} or $\mu_{A_i \cap B_i}(x,y) = \mu_{A_i}(x) \wedge \mu_{B_i}(y)$ (3.16)

- Minimum-norm fuzzy implication

[Ai(u) and Bi(v)] →Ci(w)=min{Ai(u),Bi(v),Ci(w)} or

$$\mu_{R_i}(x,y,z) = \mu_{A_i}(x) \wedge \mu_{B_i}(y) \wedge \mu_{C_i}(z) \quad (3.17)$$

- Representing each rule by an implication relation

$$\begin{aligned} \mu_{C_i^{'}}(z) &= \sup_{\substack{x \in U \\ y \in V}} t[\mu_{A_i^{'}}(x)\mu_{B_i^{'}}(y),\ \mu_{R_i}(x,y,z)] \\ &= \sup_{\substack{x \in U \\ y \in V}}[\mu_{A_i^{'}}(x) \wedge \mu_{B_i^{'}}(y) \wedge \mu_{A_i}(x) \wedge \mu_{B_i}(y) \wedge \mu_{C_i}(z)] \end{aligned} \quad (3.18)$$

- Maximum s-norm rule aggregation

$$\textbf{Agg}\ (R1, R2,\ \cdots, Rn) = max(R1, R2,\ \cdots, Rn)$$

The **Minimum Inference Engine** is obtain as

$$\mu_C(z) = \max_{i=1}^{n}[\mu_{C_i^{'}}(z)] \quad (3.19)$$

- Singleton fuzzifier

$$\mu_{A_i'}(x)=\begin{cases}1 & if\ x=x'\\ 0 & otherwise\end{cases} \text{ and } \mu_{B_i'}(x)=\begin{cases}1 & if\ y=y'\\ 0 & otherwise\end{cases} \tag{3.20}$$

Substituting (3.20) into (3.19), (3.21) is obtained as

$$\mu_C(z)=\max_{i=1}^{n}[\mu_{A_i}(x')\wedge\mu_{B_i}(y')\wedge\mu_{C_i}(z)] \tag{3.21}$$

- Center average defuzzifier

Since for a given input x' and y', the center of the i'th fuzzy set in (3.21) (that is, the fuzzy set with membership function $\min[\mu_{A_i}(x')\mu_{B_i}(y')\mu_{C_i}(z)])$ is the center of Ci, we see that the $z_i^{'}$ in (3.7) is the same in this situation. Additionally, the height of the i'th fuzzy set in (3.21), denoted C (zi) in (3.7), is min[$\mu_{A_i}(x')\mu_{B_i}(y')\mu_{C_i}(z_i^{'})$]=min[$\mu_{A_i}(x')\mu_{B_i}(y')$], (since Ci is normal). Hence, using the center average defuzzifier (3.7) for (2.21), (3.22) is obtained as

$$z'=\frac{\sum_{i=1}^{n} z_i^{'}\mu_{A_i}(x')\wedge\mu_{B_i}(y')}{\sum_{i=1}^{n}\mu_{A_i}(x')\wedge\mu_{B_i}(y')} \tag{3.22}$$

Let x'=x, y'=y, and z'= f (x, y), thus

$$f(x,y)=\frac{\sum_{i=1}^{n} z_i^{'}\mu_{A_i}(x)\wedge\mu_{B_i}(y)}{\sum_{i=1}^{n}\mu_{A_i}(x)\wedge\mu_{B_i}(y)} \tag{3.23}$$

Finally, the crisp output z of fuzzy system from crisp inputs x and y is obtained. This is also a nonlinear input-output mapping.

3.3 PI-like Fuzzy Logic Controller Design

If a fuzzy controller is designed to generate the control actions within the proportional-integral (PI) concepts like a conventional PI controller, it is called a fuzzy PI-like controller. This kind of "fuzzy PI controller" consists of a set of heuristic control rules. The control signal or the incremental change of control signal is built as a nonlinear function of the error e and change of error Δe, where the nonlinear function includes fuzzy reasoning. There are no explicit proportional, integral gains; instead the control signal is directly deduced from the knowledge base and fuzzy inference, for example, Larsen inference (eq. 3.15). A block diagram of the general PI-like FLC is shown in Figure 3.3.

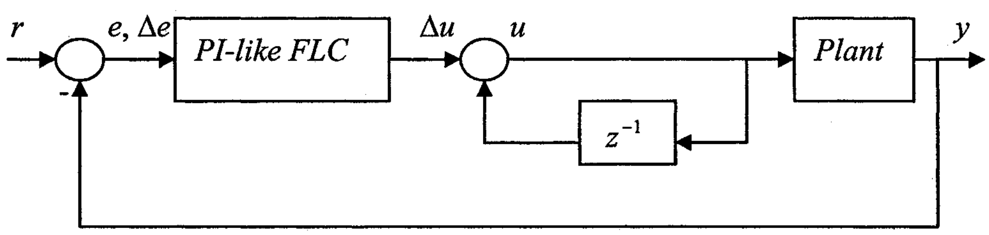

Figure 3.3: Block diagram of the PI-like fuzzy control system

A FLC has two inputs, the error $e(k)$ and change of error $\Delta e(k)$, which are defined by $e(k) = r(k) - y(k)$, $\Delta e(k) = e(k) - e(k-1)$, where r and y denote the applied set point input and plant output, respectively. Indexes k and k-1 indicate the present and the previous state of the system, respectively. The output of the FLC is the incremental change in the control signal $\Delta u(k)$. The control signal is obtained by

$$u(k) = u(k-1) + \Delta u(k) \tag{3.24}$$

All membership functions (MFs) for the controller inputs, i.e., e, Δe and incremental change in controller output, Δu are defined on the common normalized domain [-1, 1], as shown in Figure 3.4.

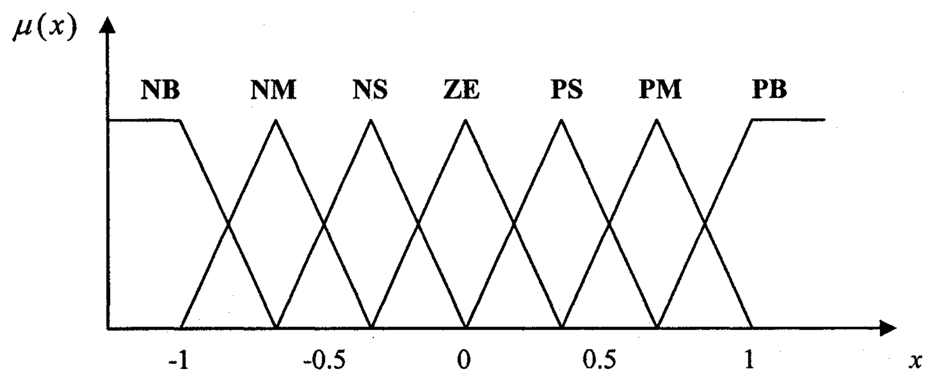

Figure 3.4: Membership functions of $e, \Delta e$ *and* Δu

The rule base for computing the output Δu is shown in Table 3.1; this is a very often used rule-base and is designed with a two-dimensional phase plane where the FLC drives the system into the so-called sliding mode [17]. The control rules in Table 3.1 are built based on the characteristics of the step response. For example, if the output is falling far away from the set point, a large control signal that pulls the output toward the set point is expected, whereas a small control signal is required when the output is near and approaching the set point.

Table 3.1: Fuzzy rules for computation of Δu

$e(k)/\Delta e(k)$	**NB**	**NM**	**NS**	**ZE**	**PS**	**PM**	**PB**
NB	NB	NB	NB	NM	NS	NS	ZE
NM	NB	NM	NM	NM	NS	ZE	PS
NS	NB	NM	NS	NS	ZE	PS	PM
ZE	NB	NM	NS	ZE	PS	PM	PB
PS	NM	NS	ZE	PS	PS	PM	PB
PM	NS	ZE	PS	PM	PM	PM	PB
PB	ZE	PS	PS	PM	PB	PB	PB

Table 3.2: Nomenclature

NB	**NM**	**NS**	**ZE**	**PS**	**PM**	**PB**
Negative Big	Negative Medium	Negative Small	ZEro	Positive Small	Positive Medium	Positive Big

Here, triangular MFs are chosen for **NM, NS, ZE, PS, PM** fuzzy sets and trapezoidal MFs are chosen for fuzzy sets **NB** and **PB**.

3.4 Incremental Fuzzy Gain Scheduling PI Controller Design

3.4.1 Conventional PID Controllers

The most widely used controllers in industry are conventional proportional-integral-derivative (PID) controllers due to their simple control structure, robust performance in a relatively wide range of operating conditions, ease of design, and inexpensive cost. The design of such a controller requires specification of three parameters: proportional gain, integral time constant and derivative time constant. The PID controllers in the literature can be divided into two main categories. In the first category, the controller parameters are fixed during control after they have been tuned or chosen in a certain optimal way. The Ziegler-Nichols tuning formula is perhaps the most well known tuning method (See Appendix A) [19]. The PID controllers of this category are simple, but cannot always effectively control systems with changing parameters, and may need frequent on-line retuning. The controllers of the second category have a structure similar to PID controllers, but their parameters are adapted on-line based on parameter estimation, which requires certain knowledge of the process, e.g., the structure of the plant model. Such controllers are called adaptive PID controllers in order to differentiate them from the first category.

The transfer function of a PID controller has the following form:

$$G_c(s) = K_p + K_i / s + K_d s \tag{3.25}$$

where *Kp*, *Ki*, and *Kd* are the proportional, integral, and derivative gains, respectively.

Another useful equivalent form of the PID controller is

$$G_c(s) = K_p(1 + 1/(T_i s) + T_d s) \tag{3.26}$$

where $T_i = K_p / K_i$ *and* $T_d = K_d / K_p$. T_i *and* T_d are known as the integral and derivative time constants, respectively.

Upon digitizing PID transfer function (3.25) using backward differences, (3.27) is obtained as

$$G_c(z) = K_p + TK_i /(1 - z^{-1}) + (K_d / T)(1 - z^{-1}) \tag{3.27}$$

where *T* is the sampling period.

The corresponding input-output form is (assuming *e (n)*=0, for *n*<0)

$$u(k) = K_p e(k) + TK_i \sum_{n=0}^{k} e(n) + (K_d / T)\{e(k) - e(k-1)\} \tag{3.28}$$

where *e (k)* is the controller input (i.e. the system error), u (k) is the controller output at time *kT*.

According to (3.28), u (k-1) can be presented as

$$u(k-1) = K_p e(k-1) + TK_i \sum_{n=0}^{k-1} e(n) + (K_d / T)\{e(k-1) - e(k-2)\} \tag{3.29}$$

Subtracting (3.29) from (3.28), gives (3.30)

$$u(k) = u(k-1) + K_p\{e(k) - e(k-1)\} + TK_i e(k) + (K_d / T)\{e(k) - 2e(k-1) + e(k-2)\} \tag{3.30}$$

So, the incremental form of (3.28) is

$$\begin{aligned} \Delta u(k) &= u(k) - u(k-1) \\ &= K_p\{e(k) - e(k-1)\} + TK_i e(k) + (K_d / T)\{e(k) - 2e(k-1) + e(k-2)\} \end{aligned} \tag{3.31}$$

According to classical control theory, the effects of individual *P/I/D* action (or gains) of a controller can be summarized as follows:

u_P : speed up response, decrease rise time, and increase overshoot.

u_I : reduce the steady state error.

u_D : increase the system damping, decrease settling time.

The parameters of the PID controller *Kp, Ki, Kd* or *Kp, Ti,* and *Td* can be manipulated to produce various response curves from a given process. However, it cannot yield a good control performance if a plant model is unknown and the plant has nonlinearities and uncertainties. Therefore, good control techniques and algorithms for tuning of the gains of the PID controllers are particularly important for the satisfactory operation of industrial control systems. In the following section, a tuning scheme for the

PI controller based on fuzzy reasoning is introduced.

3.4.2 Incremental Fuzzy Gain Scheduling PI Controller

Proposed fuzzy PI controller is composed of a conventional PI control system in conjunction with a set of fuzzy rules and a fuzzy reasoning mechanism to tune the PI gains online. By virtue of fuzzy reasoning, these types of fuzzy PI controllers can adapt themselves to varying environments. Incremental Fuzzy Gain Scheduling PI Controller (IFGSPIC) is a such type of controller.

IFGSPIC is similar to the conventional Gain Scheduling (GS) controller in changing the gains for varied operating conditions or process dynamics. When using GS controller, the abrupt changes to the parameters of the controller can lead to an unsatisfactory or even unstable control performance. However, using a fuzzy GS controller as proposed in [20, 21], it is possible to ensure that the controller parameters change in a smooth fashion. IFGSPIC provides a fuzzy logic supervised PI control scheme in which parameters of a PI controller are updated online as a function of the operational conditions of the controlled plant, improving the behavior of a classical fixed PI controller. It combines the advantages of a fuzzy logic controller and a conventional controller. The closed-loop system of IFGSPIC is shown in Figure 3.5.

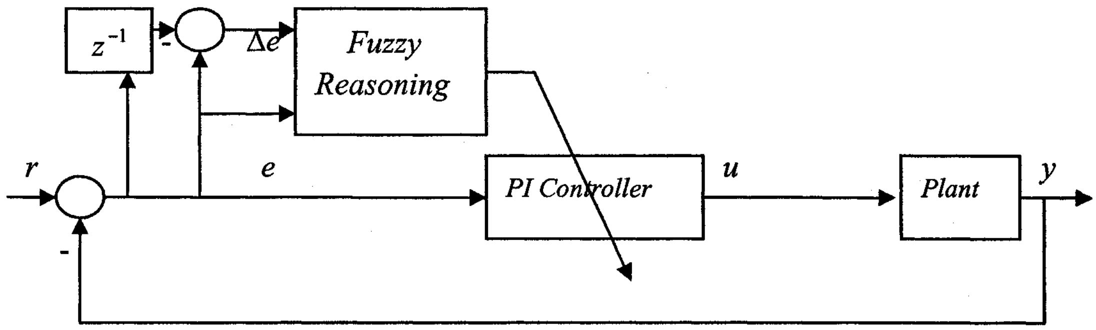

Figure 3.5: Closed-loop system of IFGSPIC

The proposed IFGSPIC controller has the following form:

$$K_p = K_{p0} + k_p CV_p(e, \Delta e) \tag{3.32}$$

$$K_i = K_{i0} + k_i CV_i(e, \Delta e) \tag{3.33}$$

$$\begin{aligned} u(t) &= K_p e(t) + K_i \int_0^t e(\tau)d\tau = [K_{p0}e(t) + K_{i0}\int_0^t e(\tau)d\tau] \\ &+ k_p CV_p(e,\Delta e)e(t) + k_i CV_i(e,\Delta e)\int_0^t e(\tau)d\tau \\ &= u_c(t) + \Delta u(t) \end{aligned} \tag{3.34}$$

where K_{p0} *and* K_{i0} represent initial proportional and integral gains obtained by a Ziegler-Nichols tuning method, and proportional and integral fuzzy-control matrices are expressed by CV_p *and* CV_i whose elements are fuzzy gains as functions of error and change of error. The fuzzy coefficients k_p *and* k_i are scaling factors.

In (3.34), there are two terms: the first term is of conventional PI control, $u_c(t)$, and the second is of incremental output type control from fuzzy reasoning, $\Delta u(t)$.

Combining the fuzzy reasoning with the conventional PI controller within the framework, the IFGSPIC can properly schedule proportional and integral gains to improve conventional PI controller's performance.

Figures 3.6-3.8 show the relational diagrams of output regions in a step response and corresponding error space. The rule base design of IFGSPIC is based on desired transient and steady state step responses. Considering the tendencies of error and sum of error terms for each region and (3.34), desired incremental output values and fuzzy-matrix elements are summarized in Table 3.3. The expected incremental output values, which

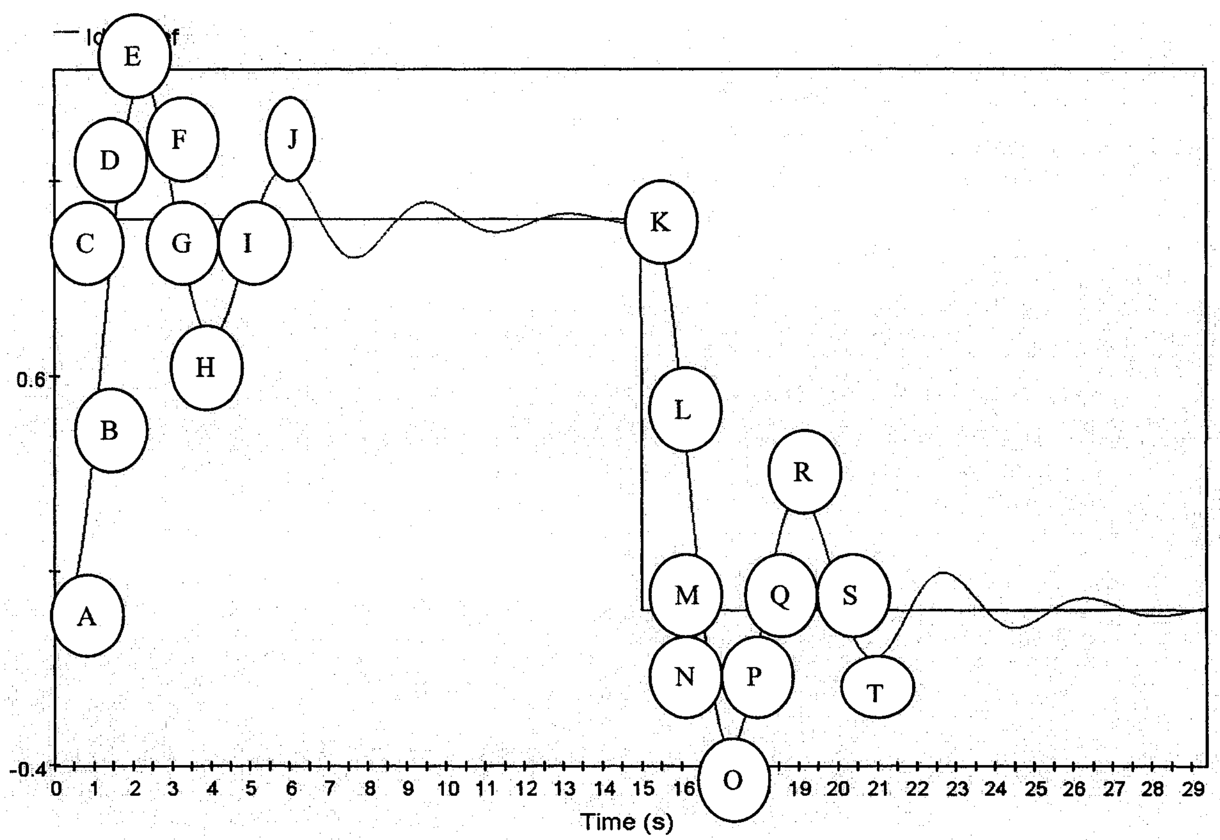

Figure 3.6: Relational diagram of output regions in step up and step down response

are the fuzzy-matrix elements, are deduced according to the tendencies of error and sum of error, as shown in Tables 3.4 and 3.5.

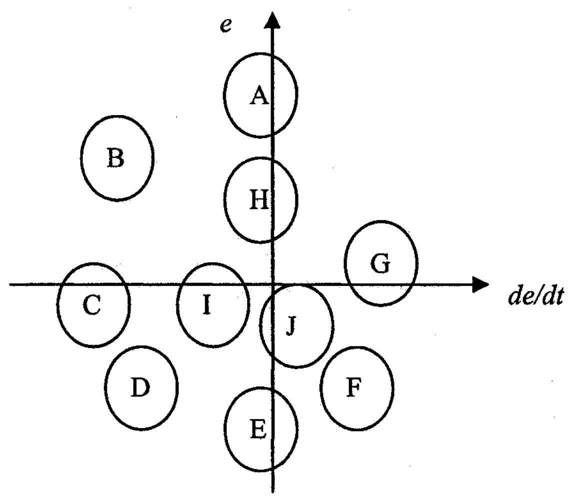

Figure 3.7: Corresponding step up error space

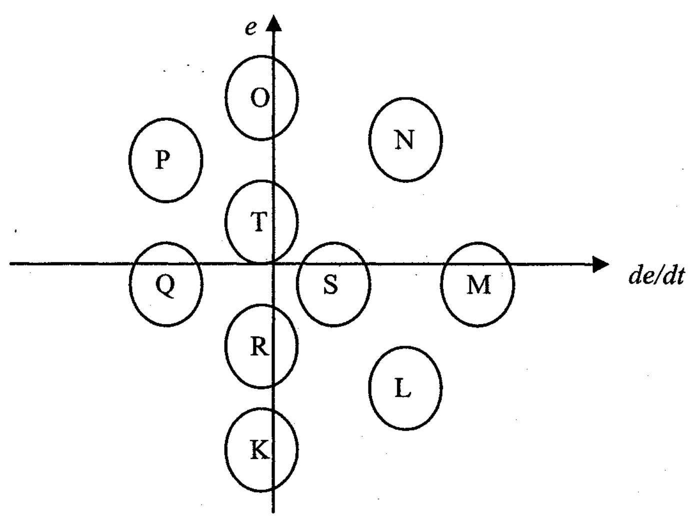

Figure 3.8: Corresponding step down error space

- **Set point step up**

While step up response increases from A to B regions, error and sum of error change from PB to PM and from ZE to PM, respectively. At this period, the system response will increase at the maximal speed. In order to avoid a large overshoot of the output value at the next period, $\Delta u(t)$ should be changed from PB to ZE to decelerate the rise in advance. Therefore, element of the proportional fuzzy matrix CV_p and element of the integral fuzzy matrix CV_i should be changed from PB to ZE. While the step up response increases from C to D regions, the error and sum of error change from ZE to NM and PB to PM, respectively. At this period, because $e(t)$ is negative and $\int e(\tau)d\tau$ is almost always positive, in order to suppress an overshoot, the element of proportional fuzzy matrix CV_p should be PB and the element of integral fuzzy matrix CV_i should be NB according to (3.34).

- **Set point step down**

For set point step down, some compromising must be done to guarantee step up response performance and disturbance rejection ability. The reason is that some corresponding cells of fuzzy matrices of set point step up and step down have some contradiction.

For set point step down, output value decreases from K to L regions, the error and sum of error change from NB to NM and from ZE to NM, respectively. Since output value decreases with maximal speed at this period and will pass under a reference value at the next period, $\Delta u(t)$ should be lowered from NB to ZE to decelerate the descent in

Table 3.3: Desired fuzzy rules for regions of a step response

Region	***e(t)***	$\int e(\tau)d\tau$	***Desired values***		
			$\Delta u(t)$	***CVp***	***CVi***
A→B	PB→PM	ZE→PM	PB→ZE	PB→ZE	PB→ZE
B→C	PM→ZE	PM→PB	ZE→NB	ZE	ZE→NB
C→D	ZE→NM	PB→PM	NM→NB	ZE→PB	NB
D→E	NM→NB	PM→PS	NB	PB→PM	NB→NS
E→F	NB→NM	PS	NB→ZE	PM→ZE	NS→ZE
F→G	NM→ZE	PS	ZE→PM	ZE	ZE→PM
G→H	ZE→PS	PS→PM	PS	ZE→PS	PM→PS
K→L	NB→NM	ZE→NM	NB→ZE	PB→ZE	NB→ZE
L→M	NM→ZE	NM→NB	ZE→PS	ZE	ZE→PB
M→N	ZE→PM	NB→NM	PS→PM	ZE→PB	PB
N→O	PM→PB	NM→NS	PM	PB	PB
O→P	PB→PM	NS	PM→ZE	PB→ZE	PB→ZE
P→Q	PM→ZE	NS	ZE→NS	ZE	ZE→NM
Q→R	ZE→NS	NS→NM	NS	ZE→PS	NM→NS

advance. In this period, $e(t)$ is negative, so the element of proportional matrix CV_p should change from PB to ZE. While $\int e(\tau)d\tau$ is almost always negative in this period, the element of integral fuzzy matrix CV_i should be positive to reinforce the control action. But in order to compromise the step up process for some contradiction as mentioned above, the element of proportional matrix CV_i should change from NB to ZE. At this moment, the proportional control plays a key role in transient response. When considering the period in which output value decreases from M to N regions, error and sum of error change from ZE to PM and NB to NM, respectively. Therefore, the element of proportional fuzzy matrix CV_p should be NB and the element of integral fuzzy matrix CV_p should be PB, but we chose both of them PB due to the reason mentioned above. The integral control plays a key role in suppressing an undershoot.

Table 3.4: Fuzzy rules for computation of CV_p

$\Delta e(k)/e(k)$	**NB**	**NM**	**NS**	**ZE**	**PS**	**PM**	**PB**
NB	PB	PB	PB	ZE	NM	NS	ZE
NM	PB	PB	PB	ZE	NS	ZE	PS
NS	PB	PB	PM	ZE	ZE	PS	PM
ZE	PB	PM	PS	ZE	PS	PM	PB
PS	PM	PS	ZE	ZE	PM	PB	PB
PM	PS	ZE	NS	ZE	PB	PB	PB
PB	ZE	NS	NM	ZE	PB	PB	PB

Through deliberately tuning the control rules, this compromise can also get better results for set point step down.

Table 3.5: Fuzzy rules for computation of CV_i

$\Delta e(k)/e(k)$	**NB**	**NM**	**NS**	**ZE**	**PS**	**PM**	**PB**
NB	NB	NB	NB	NB	NM	NS	ZE
NM	NB	NB	NB	NM	NS	ZE	PS
NS	NB	NB	NM	NS	ZE	PS	PM
ZE	NB	NM	NS	ZE	PS	PM	PB
PS	NM	NS	ZE	PS	PM	PB	PB
PM	NS	ZE	PS	PM	PB	PB	PB
PB	ZE	PS	PM	PB	PB	PB	PB

The following steps are used for the tuning of IFGSPIC:

Step1. Use Ziegler-Nichols method to obtain initial values of PI gains, K_{p0} *and* K_{i0}.

Step2. Determine initial value of IFGSPIC's proportional gain according to transient state and disturbance rejection situations. In the transient state, a large proportional gain to speed up regulation is needed, but this will be at the risk of producing a large overshoot. And in steady state, because system error is almost zero, proportional control action is near zero. Considering the above two situations, the initial value of the proportional gain can be chosen smaller than that obtained from the Ziegler-Nichols method and let the IFGSPIC readjust the proportional gain around the initial value. In this way, the system will have less overshoot and lower settling time whilst keeping the same rising time. From the point of view of disturbance rejection, it is expected that the proportional gain will be big enough. As a result, the initial proportional gain is chosen to be 1/2 to 1/3 of the value obtained from the Ziegler-Nichols method. Let this value plus the value of IFGSPIC's output be equal to the value obtained from the Ziegler-Nichols method, which has a good ability at load disturbance rejection [18]. Thus, the system's stability and the ability for anti-disturbance can be guaranteed.

Step3. Determine initial value of IFGSPIC integral gains according to steady state operation. Because integral control action is used primarily to reduce the steady state error, the initial value of the integral gain obtained from the Ziegler-Nichols method is kept unchanged. When system enters steady state, the incremental output of fuzzy reasoning is near zero, so this initial value will keep the control system at a high accuracy and less tendency to initiate system oscillations.

Proof. The random variable l given by (17) can be rewritten as:

$$l = \frac{1}{2}\sum_{i=1}^{m}(1 - \frac{1}{\lambda_i})z_i^2 = \frac{1}{2}\sum_{i=1}^{m}\kappa_i z_i^2 \tag{53}$$

where $\kappa_i = 1 - \frac{1}{\lambda_i}$ is the i^{th} weight factor. As z_i is normal, the distribution of z_i^2 is chi-square (χ^2) with one degree of freedom. Further, since $z_1, z_2, ..., z_m$ are independent and identically distributed (i.i.d), the variables $z_1^2, z_2^2, ..., z_m^2$ are i.i.d too. Now, l is a weighted sum of many i.i.d random variables z_i^2. Therefore, using the central limit theorem, l can be expected to approach the Gaussian distribution provided that M is sufficiently large. □

Using the Theorem 3.4.1, the conditional probability of SS, $p(l|H_0)$, is Gaussian for a large frame size M since the observations z_i are normal given the hypothesis H_0. Note that, the mean ($E[l|H_0]$) and variance ($Var[l|H_0]$) are given by (31) and (33), respectively. Therefore, the expression for P_f in (41) can be written as:

$$\begin{aligned} P_f &= \frac{1}{\sqrt{2\pi Var[l|H_0]}}\int_{\gamma}^{\infty} \exp\left(-\frac{(l - E[l|H_0])^2}{2Var[l|H_0]}\right)dl, \\ &= 1 - erf\left(\frac{\gamma - E[l|H_0]}{\sqrt{Var[l|H_0]}}\right). \end{aligned} \tag{54}$$

where $erf(.)$ is the standard error function defined as:

$$erf(x) \triangleq \int_{-\infty}^{x} \frac{\exp(-x^2/2)}{\sqrt{2\pi}}. \tag{55}$$

4.1 Introduction

Traditionally, HVDC transmission systems use PI controllers with fixed PI gains. Such controllers work well for perturbations within a small operating range. However, when AC systems are weak, the HVDC systems are prone to repetitive commutation failures under disturbances, which may lead to the instability and collapse of the DC link. To overcome these problems, some advanced controllers are proposed.

This chapter investigates a FL based controller for a HVDC plant under the EMTP RV simulation environment. The IFGSPIC is used for the current control of the rectifier. Performance evaluations under AC fault and set-point step change are studied. The performance comparison between the conventional PI controller and hybrid IFGSPIC is made. FLC implementation, analysis, selection and experimental results are presented.

In section 4.2, implementing fuzzy logic controllers using EMTP RV is presented. In section 4.3, the analysis and selection of fuzzy controllers is described based on simulation results. Section 4.4 presents IFGSPIC control of a HVDC plant. Finally, the effect of different scaling factors on the system's performance of the FLC is discussed in section 4.5.

4.2 Implementing Fuzzy Logic Controller Using EMTP RV

Larsen's method [22] is used for FLC design, which was introduced in section 3.2.3 (1). FLC has two inputs: error (e) and change of error (Δe) and one output: control variable (Δu). The membership functions of $e, \Delta e \; and \; \Delta u$ were shown in Figure 3.4. The rule base has 49 rules. For a different rule base design, only the centers of the fuzzy sets' of the output of the fuzzy inference engine need to be modified.

To implement this controller using EMTP RV, several building blocks in the control library of EMTP RV are used. Figure 4.1 gives the detailed scheme of the controller. Typically, a FLC has four parts (Figure 4.2): fuzzification, fuzzy rule base, fuzzy inference engine, and defuzzification. The detailed implementation of the FLC is as follows:

1. **Fuzzification** For fuzzification, there are two parts involved: error (e) fuzzification and the change of error (Δe) fuzzification. The **table** function item of the control library in EMTP RV is used for fuzzification. Since the MFs of error and the change of error are represented by seven fuzzy subsets from Negative **Big (NB)** to **Positive Big** (PB), fourteen **table** function items **(Ftb1** to **Ftb14)** are used to get these fuzzy sets, as shown in Figure 4.1. The **table** function item has an interpolation function between two given points. Linear interpolation makes it easy to obtain triangular and

trapezoidal MFs.

2. **Fuzzy rule base** From Figure 4.1, it is noted that there are 49 rules, from **w11** to **w77,** which construct the rule base (i.e. **If** *x* **and** *y*, **then** *z*).

3. **Fuzzy inference engine and defuzzification** The fuzzy inference engine and defuzzification can be formulated from a combination of **product, gain,** and **adder** items from the EMTP RV control library, based on eq. (3.15), which is repeated below for convenience.

$$f(x,y)=\frac{\sum_{i=1}^{n} z_i^{'}\mu_{A_i}(x)\mu_{B_i}(y)}{\sum_{i=1}^{n}\mu_{A_i}(x)\mu_{B_i}(y)} \tag{4.1}$$

In Figure 4.1, the **gain** blocks (**Mu1** to **Mu49**) represent the centers ($z_i^{'}$) of the fuzzy inference engine. Two-input **product** blocks (**Fm1** to **Fm49**) are used for an algebraic product fuzzy conjunction i.e. $\mu_{A_i}(x)\mu_{B_i}(y)$. The **product** blocks (Fm1 to Fm49) together with **gain** blocks (**Mu1** to **Mu49**) implement a product fuzzy implication (Larsen implication) i.e. $z_i^{'}\mu_{A_i}(x)\mu_{B_i}(y)$. **Adder** blocks (**Fm50** and **Fm51**) are used to accomplish the maximum s-norm rule aggregation i.e. $\sum_{i=1}^{n} z_i^{'}\mu_{A_i}(x)\mu_{B_i}(y)$.

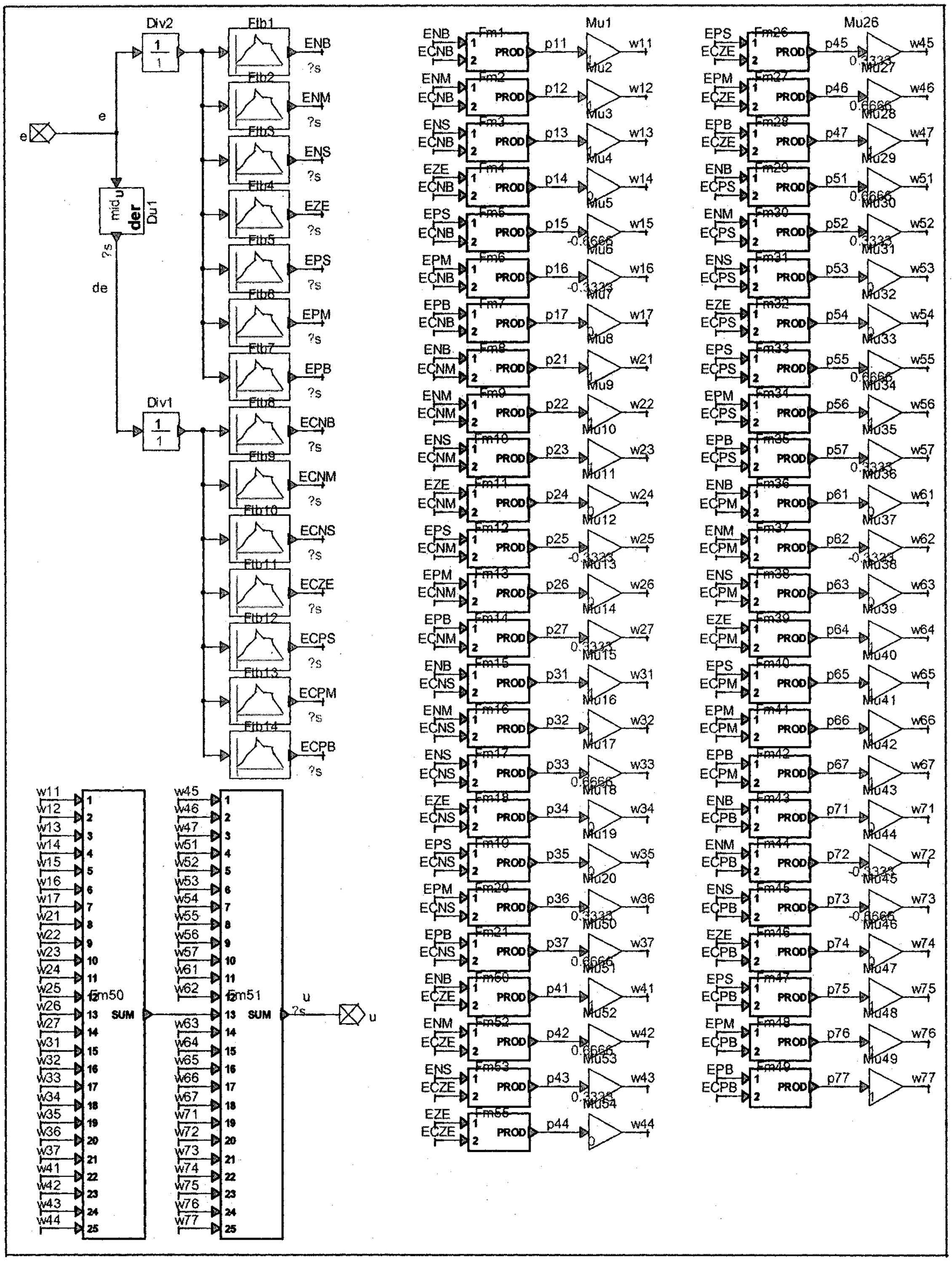

Figure 4.1: Detail scheme of FLC using EMTP RV

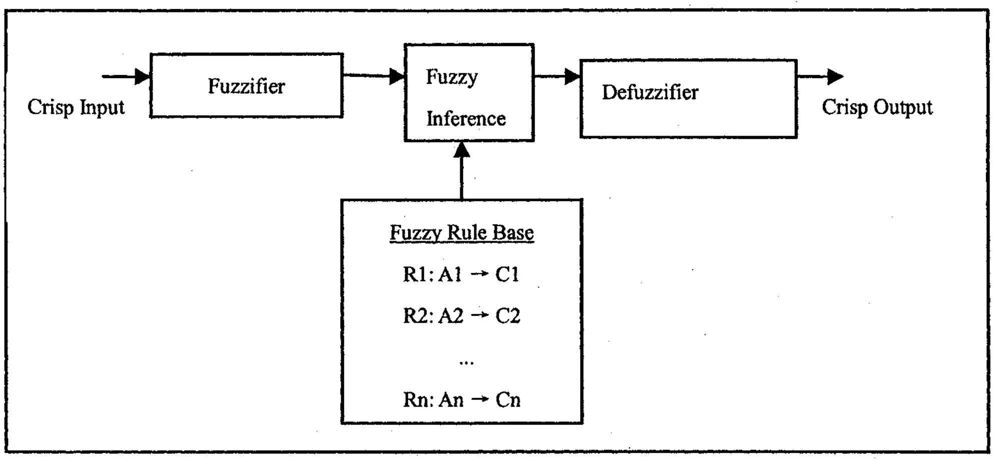

Figure 4.2: Fuzzy logic controller

It is worth emphasizing that in the closed-form eq. (4.1), Larsen's method is used. When membership functions of error and change of error $(e, \Delta e)$ have symmetrical triangles and trapezoids (i.e. with equal base and 50% overlap with neighboring membership functions), the denominator of (4.1) $\sum_{i=1}^{n} \mu_{A_i}(x)\mu_{B_i}(y)$ is equal to 1 [21]. This simplifies the computation for EMTP RV modeling and is the primary reason that Larsen's method is chosen here. It is the first time that EMTP RV has been used to implement FLC.

4.3 Analysis and Selection of Fuzzy Controllers

To examine the transient as well as the steady state behaviors of the three (PI, FLC, and IFGSPIC) controllers, a fourth-order test plant with the following transfer function is used:

$$G(s) = \frac{27}{(s+1)(s+3)^3} \tag{4.2}$$

In order to compare the performance of the controllers, the following performance measures will be used: rise time (t_r), percentage maximum overshoot (%OS), five percent settling time (t_s), integral of the squared error (ISE) and integral of the absolute error (IAE) [23]. The comparative performance of the controllers is tabulated in Tables 4.1 - 4.3.

In both cases of the FLC, Larsen inference and **center average defuzzification** are used. The Mamdani inference was also tried and no noticeable difference in control performance with these two inferences was observed. The Larsen inference method is preferred, as it is a very simple and fast algorithm, which is an important consideration for real-time implementation. During the simulation, trapezoidal method is used for the numerical integration in EMTP RV.

The initial parameters of the PI controller are determined by Ziegler-Nichols method, which are Kp=0.45 $\times$ Kr=2.304, Ti=0.85 $\times$ Tr=2.321, and Ki=Kp/Ti=0.992. The parameters Kr=5.12 and Tr=2.73 are then obtained by experiment.

The initial values of proportional and integral gains of IFGSPIC are selected to be Kp=1 and Ki=0.992. Comparing to the PI controller, the Kp of the IFGSPIC is reduced to

1 from 2.304. Considering the adaptive function of IFGSPIC, this gain reduction will lead to lower overshoot and smaller settling time whilst maintaining almost the same rise time, as shown in the analysis in the section 3.3. The initial value of integral gain, obtained from Ziegler-Nichols method, is kept unchanged. When system enters steady state, the output of IFGSPIC is zero, so that the initial value of integral gain will keep the system at high accuracy and have fewer tendencies for oscillations. Thus, IFGSPIC is also a hybrid controller: at transient state, it is a FLC to get faster response and in the steady state, it is a conventional PI controller to obtain higher accuracy.

The PI controller, FLC, STFLC, and IFGSPIC are shown in Figures 4.3 - 4.5.

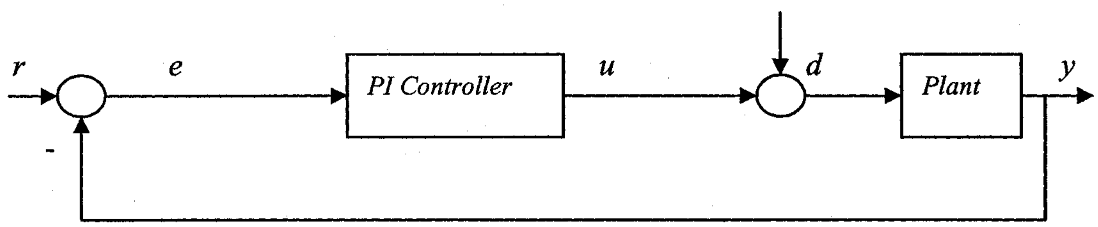

Figure 4.3: PI control system

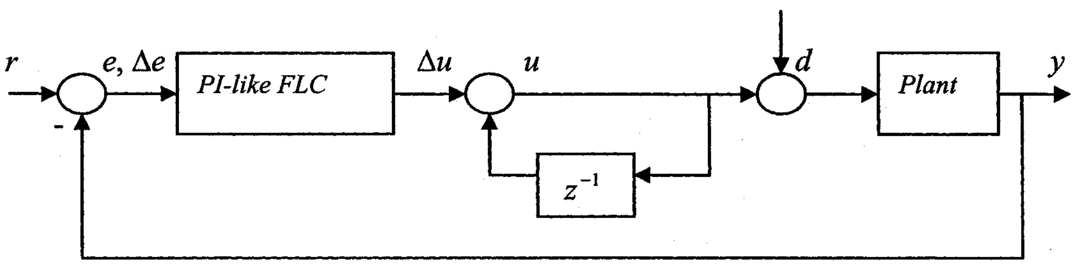

Figure 4.4: PI-like fuzzy logic control system

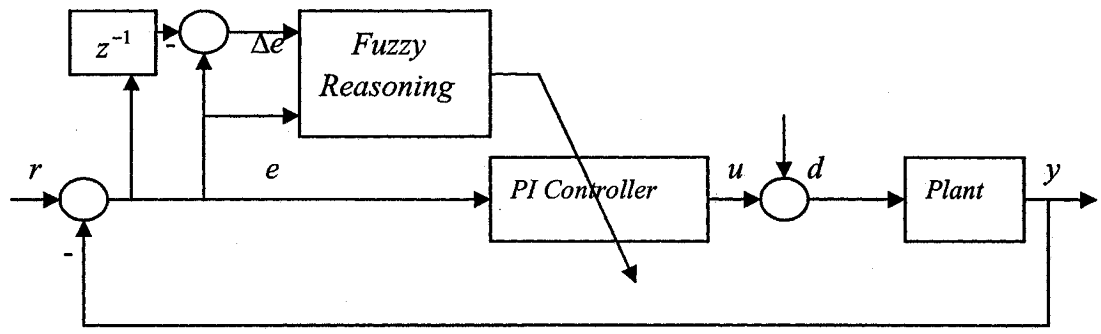

Figure 4.5: Incremental fuzzy gain-scheduling PI control system

4.3.1. Step Responses

From Table 4.1 and Figure 4.6, it can be seen that IFGSPIC has the best performance, i.e. a faster response and a smaller overshoot. From the point view of ISE and IAE performance criteria, the PI-like FLC is even worse than a conventional PI controller. There are several reasons that explain these results:

- PI-like FLC obtains the control signal incrementally starting from zero, while the IFGSPIC begins to obtain the control signal directly from the initial proportional and integral gains that has a larger output during startup.

- PI-like FLC is usually quite satisfactory for operating with lower-order systems. For higher-order systems and particularly nonlinear systems, the performance is usually poorer [24].

- PI-Like type controller has not obviously separated proportional and integral control actions and this is so-called control-action composition, i.e., they cannot decompose the output for proportional and integral control action [25].

Following the above-mentioned observations, for all further investigations, only the IFGSPIC will be considered and compared with the PI controller.

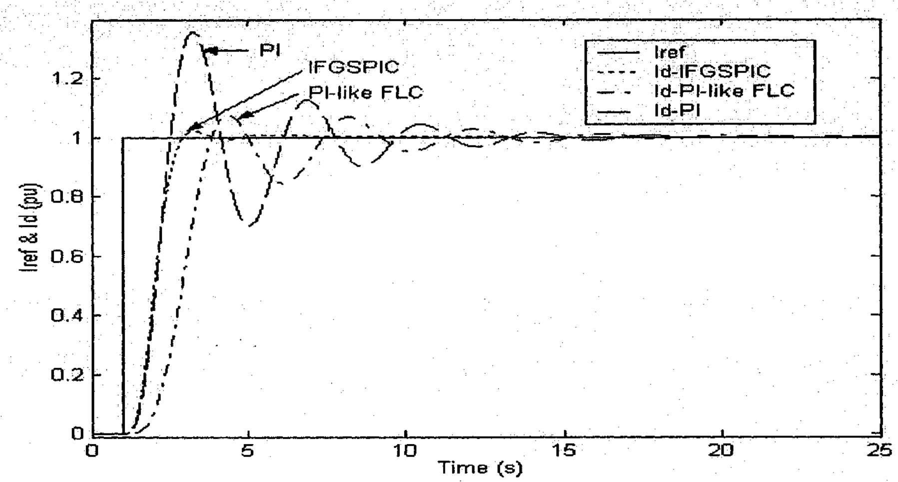

Figure 4.6: Comparison of step responses of the controllers

Table 4.1: Performance analysis for the step response

Controller type	t_r (s)	%OS	t_s (s)	ISE	IAE
PI	1.54	35.9	8.35	1.063	2.129
FLC	2.84	7.7	7.68	1.58	2.358
IFGSPIC	1.92	2.1	1.72	0.8159	1.073

4.3.2 Step Responses with Disturbance

A comparison of results from Figure 4.7 and Table 4.2 shows that the performance of IFGSPIC is consistently better than the PI controller under the disturbance d = -10 pu at 10s.

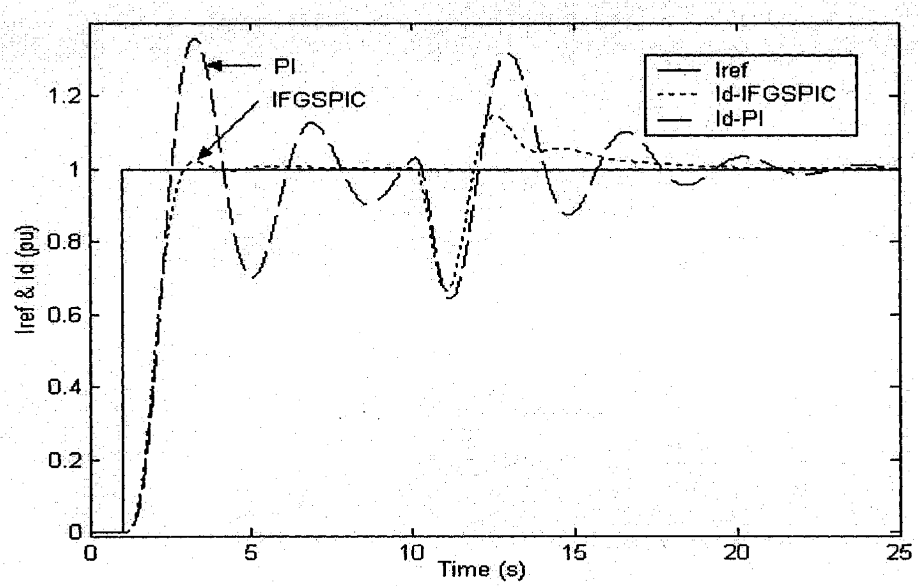

Figure 4.7: Comparison of the PI & IFGSPIC controllers under disturbance

Table 4.2: Performance analysis for the step responses with disturbance

Controller	t_r **(s)**	**%OS**	t_s **(s)**	**ISE**	**IAE**
PI	1.54	35.9	8.35	1.354	3.371
IFGSPIC	1.92	2.1	1.72	0.93	1.761

4.3.3 Responses with a 20 % Step-down in Iref

A comparison of results from Figure 4.8 and Table 4.3 shows again that the IFGSPIC outperforms the conventional PI controller with a 20% step change in Iref at 10s.

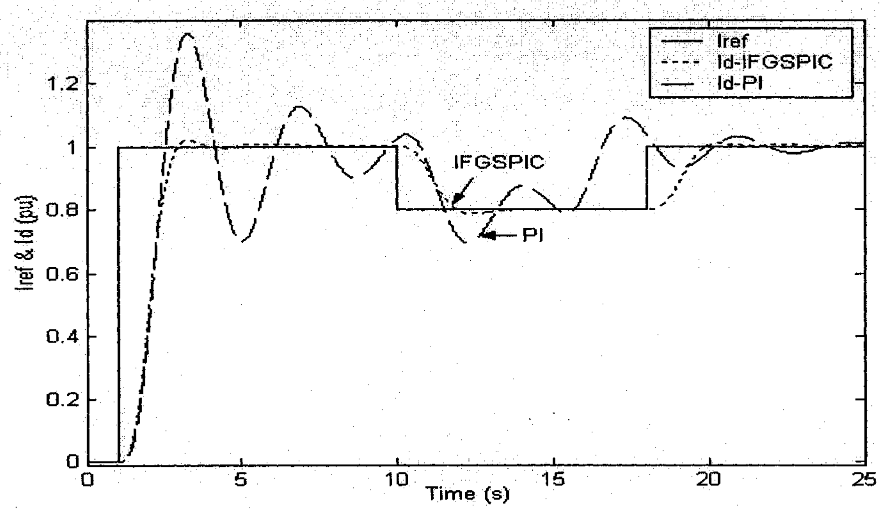

Figure 4.8: Comparison of PI & IFGSPIC controllers with step change in Iref

As a whole, IFGSPIC shows its good performance on both transient and steady state.

Table 4.3: Performance analysis for a 20% step-down in Iref

Controller	t_r (s)	%OS	t_s (s)	ISE	IAE
PI	1.54	35.9	8.35	1.159	2.89
IFGSPIC	1.92	2.1	1.72	0.8879	1.559

4.3.4 On-line Adaptation of IFGSPIC

The most important property of IFGSPIC is its ability for on-line adaptation. Figure 4.9 shows the on-line adaptation of the controller's proportional gain *Kp* and integral gain *Ki* when the system begins startup and has a 20 % step change in Iref at 10s. When the system begins startup, the controller updates *Kp* and *Ki* on-line using fuzzy inference in order to achieve a good behavior according to desired system's performance. For example, when step up response increases from zero to reference value, $\Delta u(t)$ should be changed from **PB** → **ZE** → **NB** to prevent a large overshoot and also provide a fast response. The on-line adaptation keeps the proportional gain *Kp* updated through changing the incremental output value according to fuzzy-matrix CV_p from **PB** → **ZE** and integral gain *Ki* updated through changing the incremental output value according to fuzzy-matrix CV_i from **PB** → **ZE** → **NB**. Thus $\Delta u(t)$ can follow the desired change mentioned above. It is the on-line adaptation of the parameters of IFGSPIC that guarantees that the system achieves a desired performance during transient state, thus improving the behavior of the classical fixed gain PI controllers, which are usually employed.

When the system approaches a steady state, the system's output variable converges to a reference value. As a result, error (e) approaches zero. From Figure 4.9, it can be seen that integral gain *Ki* approaches its initial value, (which was obtained from the

Ziegler-Nichols method) while proportional gain Kp does not affect steady state performance according to (4.3) when the error (e) is zero.

$$u(k) = K_p e(k) + TK_i \sum_{n=0}^{k} e(n) \tag{4.3}$$

Hence, the on-line adaptability of IFGSPIC makes the controller look like a hybrid controller. The fuzzy inference leads to a fast response when the system is in the transient state. A conventional PI controller with a set of fixed gains can be achieved after the transient stage of the process response, which can guarantee the accuracy, stability and disturbance rejection [18].

Therefore, IFGSPIC combines a fuzzy logic controller and conventional PI controller with parameters tuned by Ziegler-Nichols method. A quick response, higher accuracy and stability can be achieved by this combination.

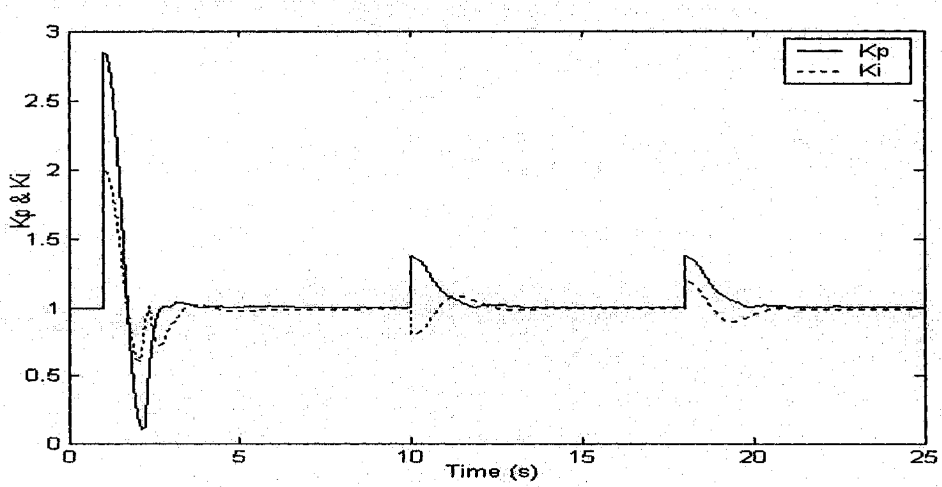

Figure 4.9: Proportional and integral gain adaptation

4.4 IFGSPIC Control of a HVDC Plant

The objective of this research is to utilize FL techniques for control of HVDC transmission systems under various disturbances. Specifically, the goal is to improve transient response performance to stabilize the system. In order to test the effectiveness of the proposed controller on the HVDC plant, both the FL and conventional methods were simulated and the results were compared with different Short Circuit Ratio (SCR) AC systems. The behavior of the controllers in controlling the desired current for a current order step change and a three-phase rectifier fault was studied.

4.4.1 Step Change in Rectifier Current Order

HVDC systems are well known for their fast controllability to transmit the desired DC power, or to modulate the DC power to improve the stability of an attached AC system. One measure of fast controllability is usually verified by considering the current reference tracking performance. Therefore, the DC link power increase or decrease can be treated as a normal disturbance. The objective of the control is to keep the system in operation with few transients in DC link power under such a disturbance.

The response of the current controllers to a relatively large step change of 30% to the current order Iref are shown in Figures 4.10, 4.11, 4.12 and 4.13. The reference is decreased from 1 to 0.7 pu at time 0.3 second and then increased back to 1.0 pu at time 0.45 second.

- **Strong System (SCR=3.8)**

From Figures 4.10 and 4.11, it can be seen that both controllers were satisfactory as the rectifier side AC system was strong. However, FL controller had a better transient performance than the PI controller.

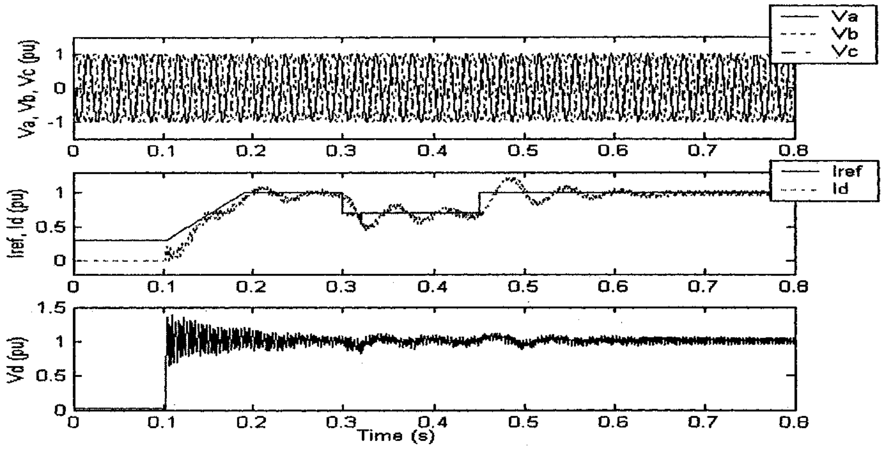

Figure 4.10: PI control for 30% step change in current order (SCR=3.8)

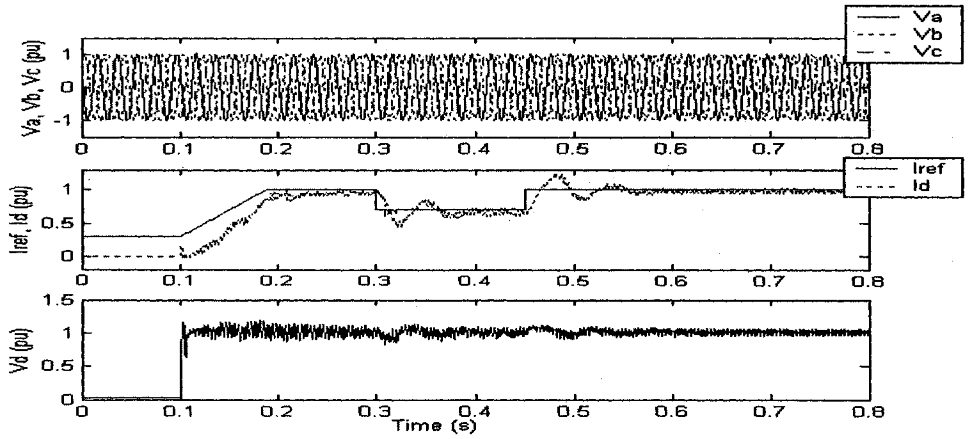

Figure 4.11: FL control for 30% step change in current order (SCR=3.8)

- **Weak System (SCR=2.3)**

When the rectifier AC system was weak, the system collapsed for the conventional controller (Figure 4.12) since multiple commutation failures took place. For the case of the FL controller (Figure 4.13), the system was able to make a quick recovery after one commutation failure. This showed the adaptability of the FL controller to the change of operating condition. Therefore, it obtained an acceptable transient response and tracking performance.

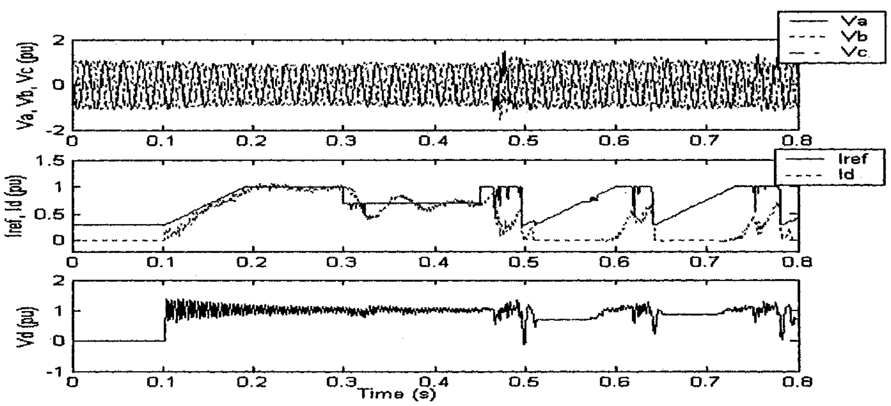

Figure 4.12: PI control for 30% step change in current order (SCR=2.3)

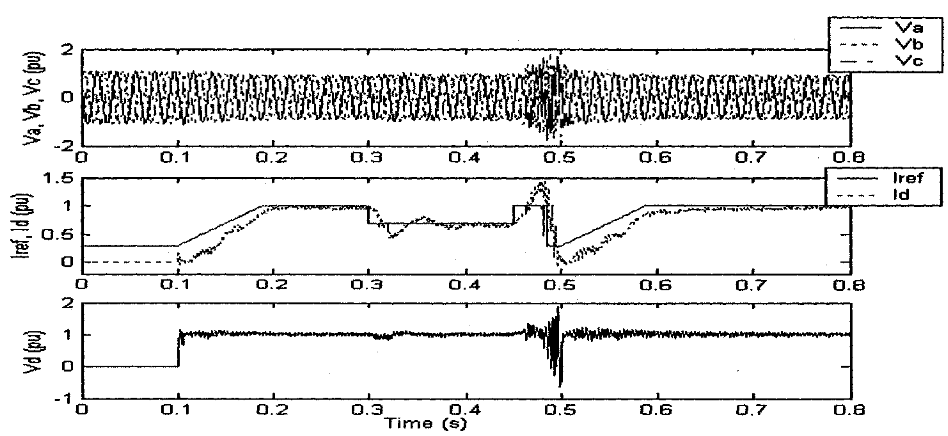

Figure 4.13: FL control for 30% step change in current order (SCR=2.3)

4.4.2 Three Phase Fault at Rectifier End

When a three phase AC voltage fault takes place at the rectifier side, it causes the loss of the DC voltage. At this time, the application of a protection circuit called the Voltage Dependent Current Limit (VDCL) is triggered. The application of the VDCL causes the current order Iref to be reduced to 0.3 pu. On recovery of the DC voltage, the current order Iref is ramped up to 1.0 pu. A three phase fault at rectifier AC bus results in commutation failure of converter valves. During the fault the DC current drops to zero. The zero current and zero power condition lead to complete collapse of the DC link. After the fault is cleared, the current controller takes actions, which influence DC link operation. Figures 4.14, 4.15, 4.16 and 4.17 show super-imposed three phase AC signals Va, Vb, and Vc, current order Iref, DC current Id, and DC voltage Vd for PI and FL controllers respectively.

- **Strong System (SCR=3.8)**

The responses of the current controllers to a three phase AC fault at the rectifier bus were shown in Figures 4.14 and 4.15 for a strong AC system. The PI controller (Figure 4.14) was able to follow the VDCL ramp but Id had large spikes and overshoots. With the FL controller (Figure 4.15), the response of the FL control was superior to that of the PI controller. Due to its adaptability, DC current Id could track VDCL better and had little or no overshoot. DC voltage Vd was smooth and had smaller amplitude oscillations. Since DC current Id had the larger oscillations under the PI control, there was a possibility that commutation failures could take place.

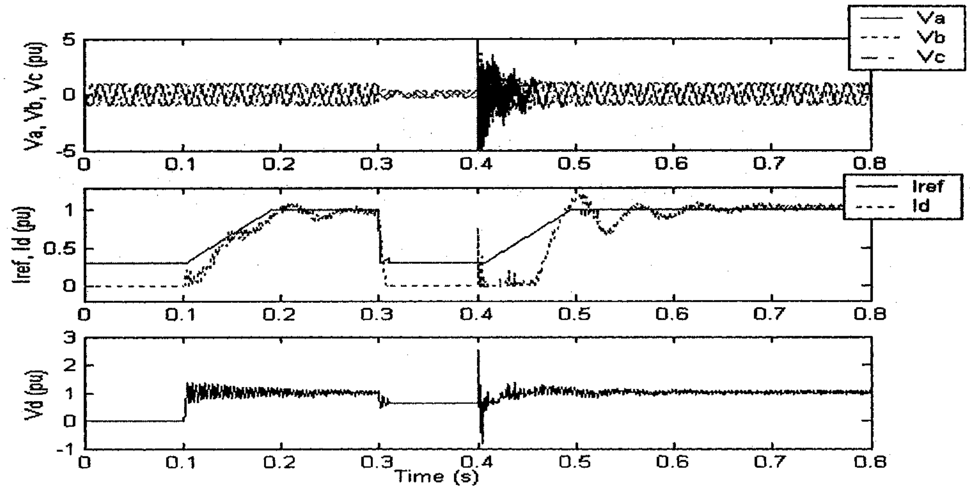

Figure 4.14: PI control for three-phase fault (SCR=3.8)

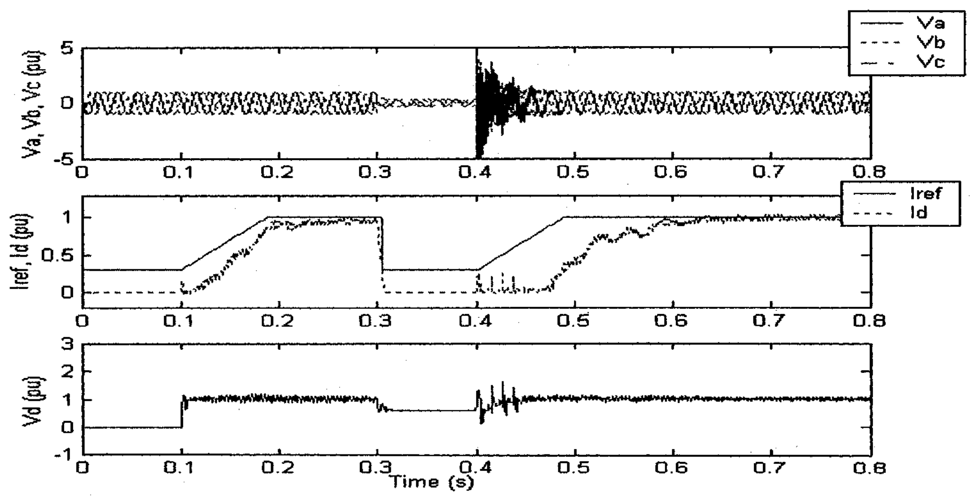

Figure 4.15: FL control for three-phase fault (SCR=3.8)

- **Weak System (SCR=2.3)**

When the rectifier AC system was weak, the system collapsed again for the conventional controller (Figure 4.16) even though it had the VDCL protection circuit. For the FL controller (Figure 4.17) it showed a much better recovery and had excellent tracking ability and faster response.

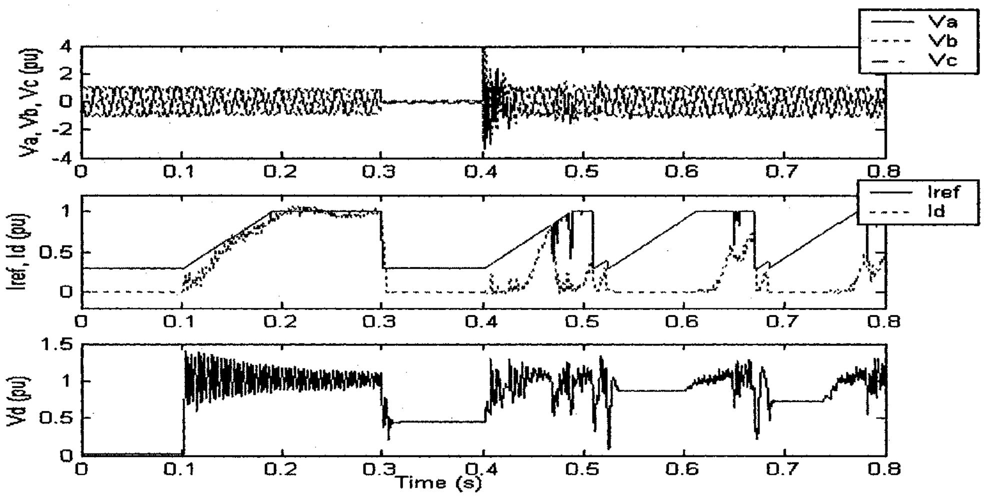

Figure 4.16: PI control for three-phase fault (SCR=2.3)

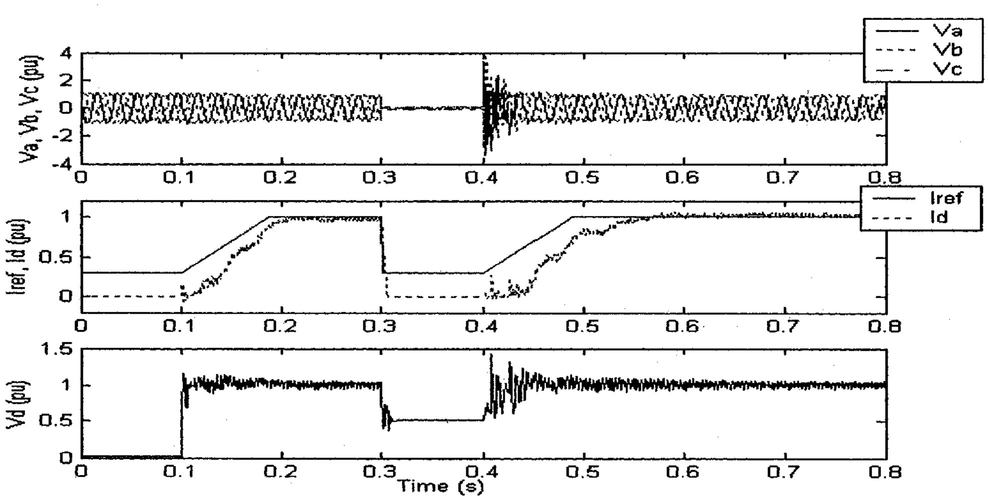

Figure 4.17: FL control for three-phase fault (SCR=2.3)

4.5 The Effect of Different Scaling Factors of FLC on the System's Performance

The use of a normalized domain requires input normalization, which maps the physical values of the process state variables into a normalized domain. In addition, output denormalization maps the normalized value of the control output variable into the physical domain. The scaling factors, which describe the particular input normalization and output denormalization, are similar to the gains of a conventional controller. They play an important role in the whole procedure since they determine the range of variation of each term. For example, if some tuning method ensures a very small rise time and a large overshoot, the integral term should have a large range of variation, whereas the other terms can remain unchanged. This range of variation should be matched with the stability interval in order to guarantee stability. Thus, scaling factors are determined from both the stability and the characteristics of the closed-loop response. They are the source of possible instabilities, oscillation problems and deteriorated damping effects [26].

The relationship between the scaling factors (G_e, $G_{\Delta e}$, $G_{\Delta u}$) and the input and output variables of the FLC is $e_N = G_e \times e$, $\Delta e_N = G_{\Delta e} \times \Delta e$, $\Delta u = G_{\Delta u} \times \Delta u_N$. Adjusting the scaling factors can alter the corresponding regions of the fuzzy sets. For example, an error equal to 0.1 may belong to PS more than to ZE as its scaling factor is increased.

Selection of suitable values of G_e, $G_{\Delta e}$, and $G_{\Delta u}$ are made based on expert's knowledge about the process to be controlled, and through trial and error [26, 27].

In general, the scaling factors provide large flexibility, but tuning scaling factors is a difficult task. Because the two-input fuzzy controllers produce the composed output ($u = f(e, \Delta e)$), this shows that each control action is a function of both error and change of error signals. This means it has input coupling. For example, the proportional action, being proportional to error signal, is also a function of its change of error signal. This makes the independent tuning of each control action (P/I) quite difficult.

Figures 18 to 24 show the effect of different scaling factors of FLC on the system's performance when it is connected to a strong AC system (SCR=3.8) for a 30% step change in current order. In order to compare the performance for different scaling factors, Figure 4.11 is reprinted as Figure 4.18 for convenience.

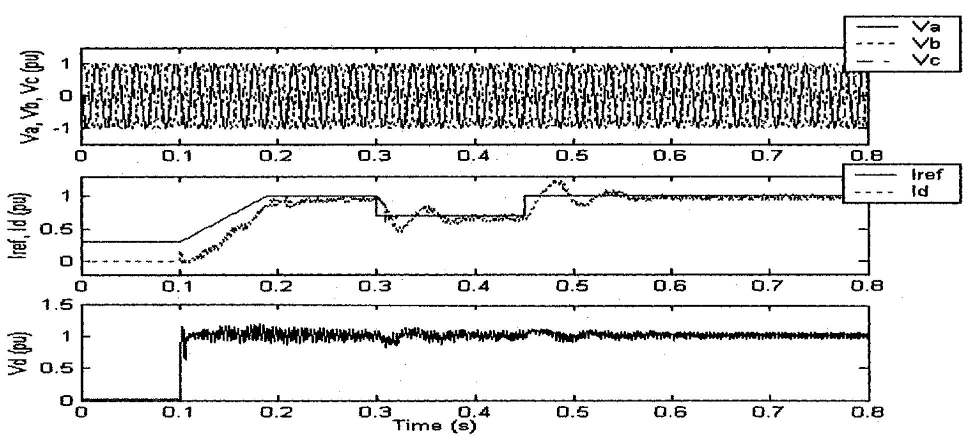

Figure 4.18: FL control for scaling factor $k_p = 0.35$, scaling factor $k_i = 0.1$

4.5.1 Comparing Different Scaling Factors of Proportional Control

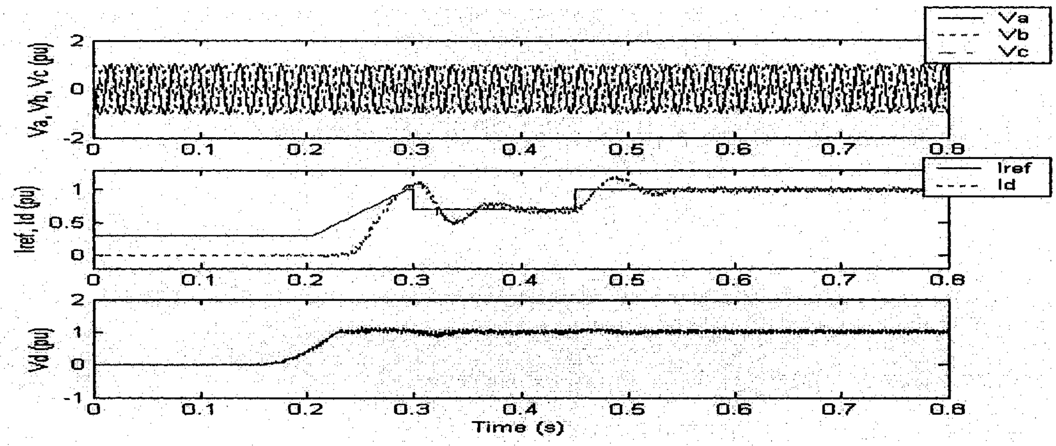

Figure 4.19: FL control for scaling factor $k_p = 0.1$, scaling factor $k_i = 0.1$

Comparing Figure 4.19 with Figure 4.18, it shows that when the scaling factor is $k_p = 0.1$, the system response is slower than that when the scaling factor is $k_p = 0.35$. For $k_p = 0.35$, the system has a fast response at 0.1 second, while for $k_p = 0.1$, the system begins to follow reference at 0.25 second. It illustrates that the proportional action is not enough for $k_p = 0.1$.

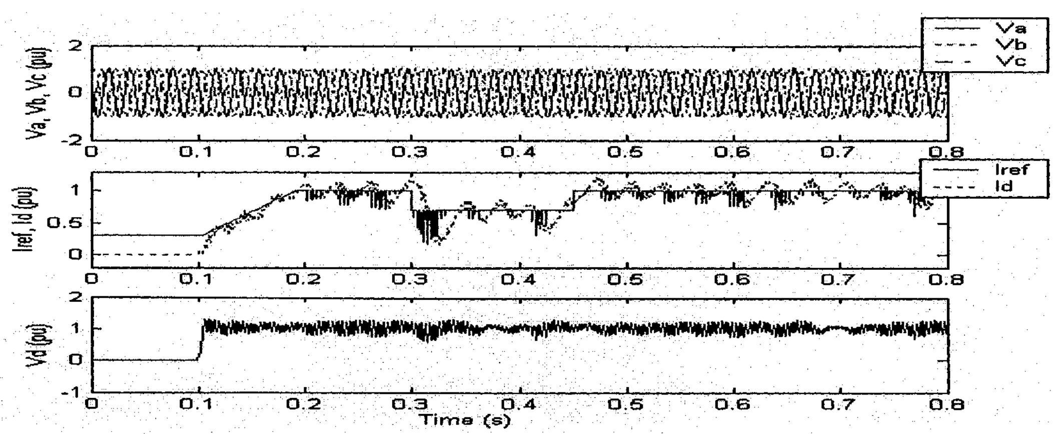

Figure 4.20: FL control for scaling factor $k_p = 10$, scaling factor $k_i = 0.1$

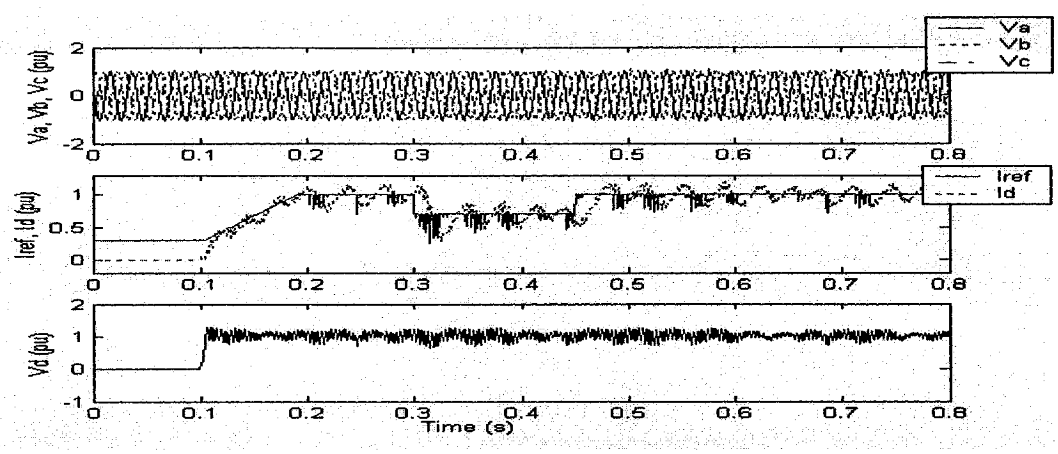

Figure 4.21: FL control for scaling factor $k_p = 20$, scaling factor $k_i = 0.1$

Comparing Figures 4.20 and 4.21 with Figure 4.18, it can be observed that when increasing scaling factor k_p, the system has fast response, but also has a tendency towards oscillations. It illustrates that the too large a proportional action causes big an overshoot and may even lead to unstable operation.

4.5.2 Comparing Different Scaling Factors of Integral Control

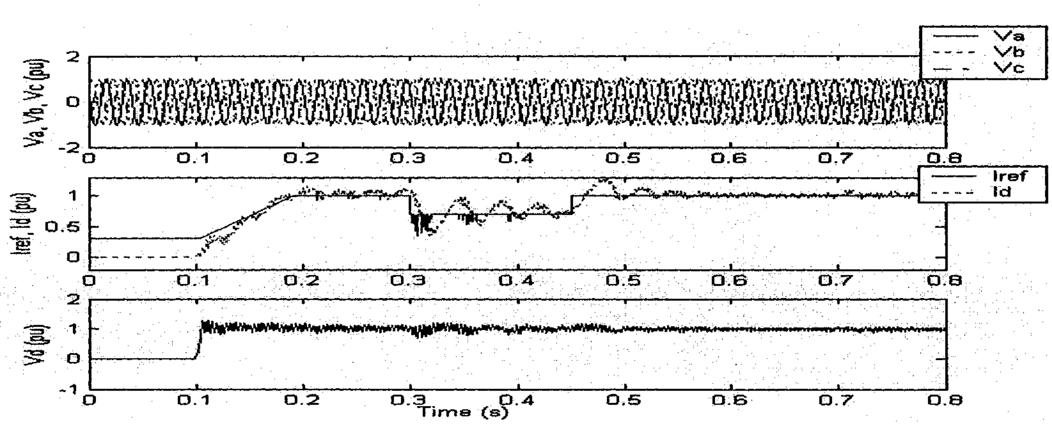

Figure 4.22: FL control for scaling factor $k_p = 0.35$, scaling factor $k_i = 10$

When the scaling factor k_i is increased to 10 (Figure 4.22), the system has more oscillations when compared with a scaling factor $k_i = 0.1$.

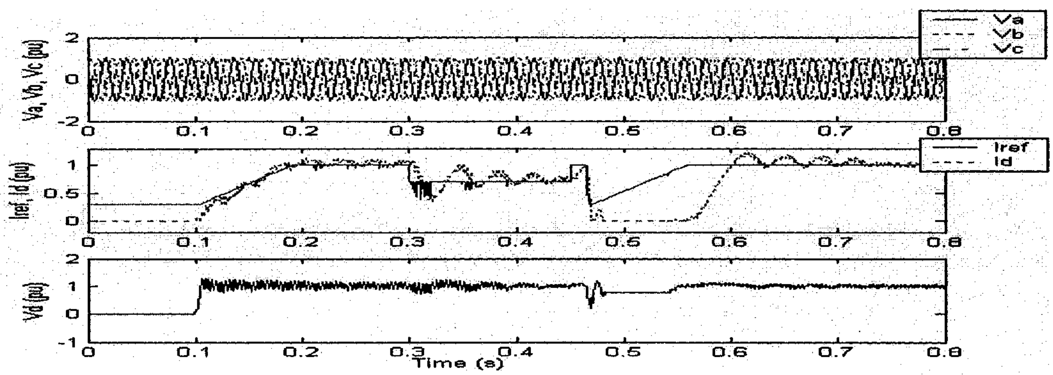

Figure 4.23: FL control for scaling factor $k_p = 0.35$, scaling factor $k_i = 20$

When the scaling factor k_i increases to 20 (Figure 4.23), it can be seen that commutation failures take place. The main function of integral control is to reduce the steady state error, but too large an integral gain will degrade transient performance and even cause system unstable operation.

4.5.3 Scaling Factors $k_p = 0$, $k_i = 0.25$ and Initial Proportional Gain $K_{p0} = 0.35$

In Figure 4.24, the proportional scaling factor k_p is set to zero, and initial proportional gain K_{p0} increases to 0.35 from 0.1. The system collapses after a step change. This shows the adaptive ability of FLC again. The small change of fixed gain (K_{p0} change from 0.1 to 0.35) leads to the instability of system, while the large change of scaling factor (k_p changed from 0.1 to 20) can still keep the system working.

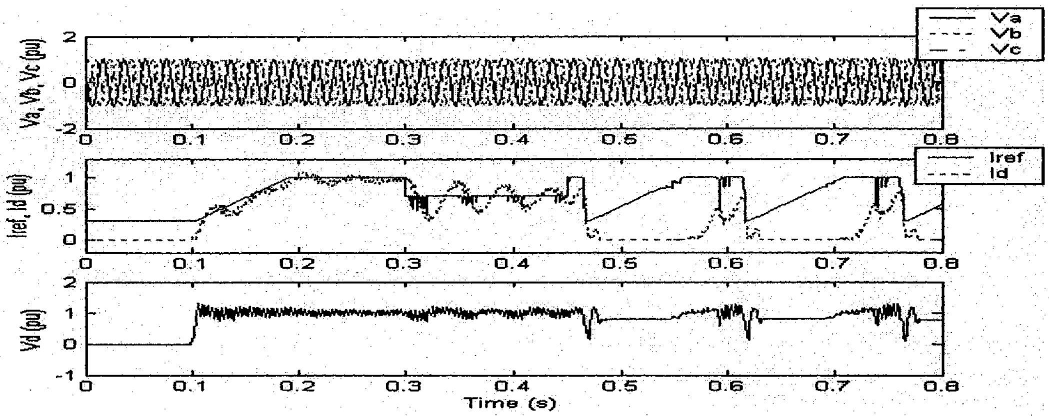

Figure 4.24: FL control for scaling factors $k_p = 0$, $k_i = 0.25$ and $K_{p0} = 0.35$

Since limited knowledge or design guidelines are available regarding implementation aspects, fuzzy control design usually requires a significant amount of "trial and error" work. It has also been experimentally observed that this kind of FLC with constant scaling factors and a limited number of **If–then** rules may have limited performance [28]. A systematic design of fuzzy controllers is of great interest. As a result, there has been significant research on the tuning of FLCs where either the input or output scaling factors, or the definitions of the MFs and sometimes the control rules are tuned to achieve the desired control objectives [28-30]. Recently, numerous papers have explored the integration of genetic algorithms or neural networks with fuzzy systems in so-called genetic fuzzy or neuro-fuzzy systems. Many publications are concerned with the design of FLCs by tuning the rule bases, MFs, and scaling factors [31-36] and have some promising results.

in this case, $S = 100 - P$) in the ROC is equivalent to random guessing. Hence, the higher the ROC curve from the line $S = 100 - P$, the better the performance of the detector is [23].

The ROC curves of the proposed detectors in babble, car, F-16 cockpit and tank noises are shown in Figs. 15, 16, 17 and 18 for -10, 0, 15 and 30 dB SNRs, respectively. For the babble and F-16 cockpit noises, it can be observed from Fig. 15 and 18 that the performance of all detectors is extremely good or poor in high or low SNR, respectively. This result is similar to the overall detection rate presented in the last section, as it shows that the task of voice activity detection is very easy at high SNR, and increasingly difficult with the lowering of the SNR. Comparing Figs. 15 and 18, it is seen that while the performance of the CVAD-NP is better than CVAD-CNP at 30 dB SNR for all noises, the CVAD-CNP does better than CVAD-NP at -10 dB SNR. Further, from Figs 15, 16, 17 and 18, it is also seen that the ROC curves for CVAD-CNP rise at a faster rate in comparison to CVAD-NP or CVAD-Bayesian, suggesting that the pause detection capability of CVAD-CNP is the best among the three CVADs. On the other hand, it can be seen that the CVAD-NP curve crosses the CVAD-CNP in most cases and, climbs a greater vertical distance, suggesting that the speech detection capability of CVAD-NP is better than CVAD-CNP or CVAD-Bayesian.

4.5 Activity Burst Corruption

The ABC parameter for the proposed VADs and AMR VADs is shown in Fig. 19 (a), (b), (c) and (d) for babble, car, F-16 cockpit and tank noises, respectively. It is useful to note that the ABC is closely related to speech detection rate but independent of overall detection rate. Hence, the ABC scores must not be judged in isolation, but

5.1 Conclusions

This thesis investigates a Fuzzy Logic (FL) based current controller for a High Voltage Direct Current (HVDC) plant connected to weak AC systems. The system is tested using the EMTP RV simulation environment. A typical HVDC system is modeled with the detailed representation of the converter, converter transformer and AC/DC filters. An Incremental Fuzzy Gain Scheduling Proportional and Integral Controller (IFGSPIC) is proposed for the current control of the rectifier. The current error and its derivative are taken as the two parameters necessary to adapt the proportional (P) and integral (I) gains of the controller based on fuzzy reasoning. A Larsen reference engine, center average defuzzification and most natural and unbiased membership functions (MFs) (i.e. symmetrical triangles and trapezoids with equal base and 50% overlap with neighboring membership functions) are used. This simplifies the controller design and reduces computation time under the EMTP RV simulation environment. Two different fuzzy rule bases are designed to tune the PI gains independently. The fuzzy control rules and analysis of IFGSPIC are presented.

To improve performance, the IFGSPIC is designed like a hybrid controller with the initial values of the proportional (P) and integral (I) gains of IFGSPIC determined by the Ziegler-Nichols tuning method. This combines the advantages of a FLC and a conventional PI controller. During transient states, the PI gains are adapted by the

IFGSPIC to damp out the transient oscillations and reduce settling time. During the steady state, the controller is automatically switched to the conventional PI controller to maintain system stability and accuracy.

The performance comparison is made in terms of criteria such as rise time (*tr*), percentage maximum overshoot (%OS), five percent settling time (*ts*), integral of the absolute error (IAE) and integral of the squared error (ISE). Results show that the proposed controller outperforms its conventional counterpart in each case.

A thorough simulation study has been conducted for a HVDC plant using the proposed controller and the conventional PI controller under AC fault and set-point step change tests. The simulation results showed that the robustness and adaptability of the proposed FL controller is better. For a strong AC system, both controllers have an acceptable performance. But when the AC system is weak, the system is prone to collapse with the conventional controller while the FL controller has a satisfactory performance. The effect of different scaling factors of FLC on the system's performance is also discussed.

5.2 Suggestions for Future Research Work

The investigation of FLC for HVDC systems in this thesis leads to several possibilities for future research:

- The FLC can be used in the inverter side for voltage control though a redesign of the fuzzy rule bases.
- Since limited knowledge or design guidelines are available, FLC design usually requires a significant amount of "trial and error" work, which implies that it is often hard to obtain optimal performance. The integration of genetic algorithms or neural networks with fuzzy systems in so-called genetic fuzzy or neuro-fuzzy systems is a trend for the systematic FLC design, where either the input or output scaling factors, or the definitions of the MFs and sometimes the control rules are tuned using genetic algorithms or neural networks to achieve the desired control objectives.

Appendix A

Ziegler-Nichols Tuning Method

In the Ziegler-Nichols technique, the parameter tuning is based on the stability limits of a system. The derivative and integral terms are initially put out of the system and proportional gain is increased until the critical oscillation point (critical gain Kr and period Tr). Then the P, PI, PID controller parameters are selected as follows:

	K	Ti	Td
P	0.5Kr		
PI	0.45Kr	0.85Tr	
PID	0.6Kr	0.5 Tr	0.125Tr

Proportional control parameter Kp=K, integral control parameter Ki=K/Ti, derivative control parameter Kd=K*Td.

Appendix B

HVDC Transmission System Data

- **Rectifier End**

Data for the AC filter at the rectifier end (230kV) is:

n	11^{th}	13^{th}	high pass
R (ohms)	0.63	0.63	82.6
L (H)	0.02783	0.01952	0.003846
C (uF)	3.009	3.009	4.573

The equivalent impedances at rectifier end AC system:

SCR	R (ohms)	L (H)
3.8 (88 deg)	0.25	0.062
2.3 (88.7 deg)	0.25	0.103

- **DC Subsystem**

  L = 0.35 H, R = 2.5 ohms

  Vd = 440 kV, Id = 1600 A, Pd = 704 MW

  DC filter: R = 1 ohm, L = 0.2814 H, C = 1uF

- **Transformers**

  Y-Y: 230/205.45 kV

  Y-Δ: 230/205.45 kV

  Impedance = 16.43 ohms

Appendix C

Electro-Magnetic Transient Program

Electro-Magnetic Transient Program (EMTP) is a circuit-oriented simulator which has been developed specifically for power system modeling. It contains many libraries such as transformers, HVDC, switches, machines, and control devices etc. Trapezoidal, Backward Euler, and Trapezoidal and Backward Euler methods are used for numerical integration with a fixed time step. Switches are treated as ideal. It is better suited for modeling high-power electronics in power systems (FACTS and HVDC).

Please visit EMTP website for more details:

www.emtp.com

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List of Publications Resulting from This Work

1. Jian Qi, V.K. Sood, V. Ramachandran, "Incremental Fuzzy PI Control of a HVDC Plant," *IEEE International Conference on Control Applications (CCA05),* Toronto, ON, Canada on August 28-31, 2005.

2. Jian Qi, V. K. Sood, V. Ramachandran, "Modeling a Fuzzy Logic Controller for Power Converters in EMTP RV," *6th International Conference on Power System Transients (IPST'2005),* Montreal, QC, Canada on June 19-23, 2005.