Chapter 4

Proposed Control Strategies

4.1 Introduction

It is necessary to achieve better frequency control than is obtained by the speed governor system itself. To accomplish this we must manipulate the speed change in accordance with some suitable control strategy. Before we do so, it is necessary to settle for a set of control specifications the stringency of which will in the end determine the quality of the proposed control method.

Here follows some realistic specifications:

- The control loop must be characterized by a sufficient degree of stability.
- Following a step load change, the frequency error should return to zero. This is referred to an isochronous control.
- The magnitude of the transient frequency deviation should be minimized. (This magnitude depends, of course, upon the magnitude of the load change.)
- The integral of the frequency error should not exceed a certain maximum value.
- The individual generator of the control area should divide the total load for optimum economy

Let us comment on each of these requirements:

- Stability is always a problem in closed-loop control. The tighter the error specifications, the greater the risk that the proposed loop will turn unstable.

- Isochronous control guarantees that the static frequency error following a step load change will vanish. No control system can, however, eliminate the transient frequency error.
- The first two specifications are taken care of by a control system with a response time of the order of a few seconds or half a minute. When these primary control requirements are met, one attends to the secondary economic requirement. This is usually being done by a slower economic dispatch control scheme, having response times of the order of a minute or longer.

The most important contribution modern optimal control theory has made to the control engineer is the ability to handle a large multivariate control problem with ease. The engineer has only to represent the control system in state variable form and specify the desired performance mathematically in terms of a performance index to be minimized. Well proven theories and techniques are available which generate a unique or best controller in the sense of minimizing the performance index.

In this chapter, three different methods to tackle load frequency control problem have been proposed. First, the problem is solved using linear quadratic regulator design based on modern control theory which minimizes a performance index to give an optimal solution in terms of feedback gain matrix and eigen values. Secondly, fuzzy logic based integral control is developed in order to give integral gain such that the dynamic parameters i.e. settling time and peakovershoot are obtained for two area and three area system. Lastly by using fuzzy logic based integral control but with HVDC link connected in parallel to existing AC tie-line.

4.2 Linear Quadratic Optimal Control Regulator

We consider a linear time-invariant system

$$\frac{dt}{dt} = \begin{bmatrix} \frac{dx_1}{dt} \\ \frac{dx_2}{dt} \\ \vdots \\ \frac{dx_{n-1}}{dt} \\ \frac{dx_n}{dt} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n-1} & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n-1} & a_{2n} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ a_{n-11} & a_{n-12} & \cdots & a_{n-1n-1} & a_{n-1n} \\ a_{n1} & a_{n2} & \cdots & a_{nn-1} & a_{nn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{n-1} \\ x_n \end{bmatrix}$$

$$+ \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1m-1} & b_{1m} \\ b_{21} & b_{22} & \cdots & a_{2n-1} & a_{2n} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ b_{n-11} & b_{n-12} & \cdots & b_{n-1m-1} & b_{n-1m} \\ b_{n-1} & b_{n2} & \cdots & b_{nm-1} & b_{nm} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_{m-1} \\ u_m \end{bmatrix}, \qquad x(t_0) = x_0,$$

or

$$\dot{x}(t) = Ax + Bu, x(t_0) = x_0, \tag{4.1}$$

where A $\in \mathbf{R}^{n \times n}$ B $\in \mathbf{R}^{n \times m}$ are the constant-coefficient matrices.

The quadratic performance functional is given as

$$J(x(\cdot), u(\cdot)) = \frac{1}{2}\int_{to}^{tf}(x^T Qx + u^T Ru)dt, Q \geq 0,\ R > 0, \tag{4.2}$$

where $Q \in \mathbf{R}^{n \times n}$ is the positive semi-definite, constant-coefficient weighting matrix and $R \in \mathbf{R}^{m \times m}$ is the positive-definite, constant-coefficient weighting matrix.

The availability of finite state and control "energies" are represented by the terms $x^T Q x$ and $u^T Ru$. The state and control variables must satisfy certain constraints because the states and control must evolve in admissible envelopes.

Then, from equation (4.1) and (4.2), we have the expression for the Hamiltonian function as

$$\mathrm{H}\left(x,u,\frac{\partial V}{\partial x}\right)=\frac{1}{2}(x^T Qx+u^T Ru)+\left(\frac{\partial V}{\partial x}\right)^T (Ax+Bu), \tag{4.3}$$

And the Hamilton-Jacobi functional equation is

$$-\frac{\partial V}{\partial t}=\min_u\left[\frac{1}{2}(s^T Qx+u^T Ru)+\left(\frac{\partial V}{\partial x}\right)^T (Ax+Bu)\right].$$

The derivative of the Hamiltonian function, one finds the following optimal controller:

$$\mathrm{u}=-R^{-1}B^T\frac{\partial V}{\partial x}. \tag{4.4}$$

This control law is found by minimizing the quadratic performance index (equation (4.2)). It must be emphasized that the second-order necessary condition for optimality is guaranteed. The weighting matrix R is positive-definite, and we have

$$\frac{\partial^2 H(x,u,\frac{\partial V}{\partial x})}{\partial u\times\partial u^T}=R>0.$$

Plugging the controller equation (4.4) into equation (4.3) or in the Hamilton-Jacobi functional equation

$$-\frac{\partial V}{\partial t}=\min_u\left[\frac{1}{2}(x^T Qx+u^T Ru)+\left(\frac{\partial V}{\partial x}\right)^T (Ax+Bu)\right],$$

one obtains the following Hamilton-Jacobi-Bellman partial differential equation:

$$-\frac{\partial V}{\partial t}=\frac{1}{2}\left(x^T Qx+\left(\frac{\partial V}{\partial x}\right)^T BR^{-1}B^T\frac{\partial V}{\partial x}\right)+\left(\frac{\partial V}{\partial x}\right)^T Ax-\left(\frac{\partial V}{\partial x}\right)^T BR^{-1}B^T\frac{\partial V}{\partial x}$$

$$=\frac{1}{2}x^T Qx+\left(\frac{\partial V}{\partial x}\right)^T Ax-\frac{1}{2}\left(\frac{\partial V}{\partial x}\right)^T BR^{-1}B^T\frac{\partial V}{\partial x}. \tag{4.5}$$

This equation must be solved. To find the solution, we assume that equation (4.5) is satisfied by the quadratic return function *V(x).* That is,

$$V(x) = \frac{1}{2} x^T k(t) x, \tag{4.6}$$

Where K ∈ $\mathbf{R}^{nxn}$ is the symmetric matrix,

$$K = \begin{bmatrix} k_{11} & k_{12} & \cdots & k_{1n-1} & k_{1n} \\ k_{21} & k_{22} & \cdots & k_{2n-1} & k_{2n} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ k_{n-11} & k_{n-12} & \cdots & k_{n-1n-1} & k_{n-1n} \\ k_{n1} & k_{n2} & \cdots & k_{nn-1} & k_{nn} \end{bmatrix}, \ k_{ij} = k_{ji.}$$

That is,

$$V(x) = \frac{1}{2} \begin{bmatrix} x_1 & x_2 & \cdots & x_{n-1} & x_n \end{bmatrix} \begin{bmatrix} k_{11} & k_{12} & \cdots & k_{1n-1} & k_{1n} \\ k_{21} & k_{22} & \cdots & k_{2n-1} & k_{2n} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ k_{n-11} & k_{n-12} & \cdots & k_{n-1n-1} & k_{n-1n} \\ k_{n1} & k_{n2} & \cdots & k_{nn-1} & k_{nn} \end{bmatrix} \times \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{n-1} \\ x_n \end{bmatrix}$$

The unknown matrix K must be positive-definite because positive semi definite and positive-definite constant-coefficient weighting matrices Q and R have been used in the performance functional (equation (4.2)). The positive definiteness of the quadratic return function *V(x)* can be verified using the Sylvester criterion (successive principal minors of K must be positive). Taking note of equation (4.6) and using the matrix identity $x^T KAx = \frac{1}{2} x^T (A^T K + KA)x,$ from equation (4.5), one has

$$-\frac{\partial\left(\frac{1}{2} x^T Kx\right)}{\partial t} = \frac{1}{2} x^T Qx + \frac{1}{2} x^T A^T Kx + \frac{1}{2} x^T KAx - \frac{1}{2} xKBR^{-1}B^T Kx. \tag{4.7}$$

The boundary conditions is

$$\mathrm{V}\left(t_f, x\right) = \frac{1}{2} x^T K\left(t_f\right) x = \frac{1}{2} x^T K_f x. \tag{4.8}$$

From equation (4.7) and equation (4.8), one concludes that the following nonlinear differential equation (the so-called Riccati equation) must be solved to find the unknown symmetric matrix K:

$$-K = Q + A^T K + KA - KBR^{-1}B^T K, K\left(t_f\right) = K_f. \tag{4.9}$$

Using equation (4.4) and equation (4.6), the controller is found as

$$\mathrm{u} = -\ R^{-1}B^T Kx. \tag{4.10}$$

Here, the matrix B is found using (4.1), the weighting matrix R is assigned by the designer by synthesizing the performance functional (4.2), and the matrix K is obtained by solving the Ricatti equation (4.9). From equation (4.10), one concludes that the feedback gain matrix is

$$K_F = -R^{-1}B^T K,$$

and the feedback coefficients are derived by solving equation (4.9). Augmenting equation (4.1) and equation (4.10), we have

$$\dot{x}(t) = Ax + Bu = Ax - BR^{-1}B^T Kx = \left(A - BR^{-1}B^T K\right)\ x$$

$$= \left(A - BK_F\right)x. \tag{4.11}$$

The closed loop system (4.11) is stable and the eigenvalues of the matrix $\left(A - BR^{-1}B^T K\right) = \left(A - BK_F\right) \in\ R^{n\times n}$ have negative real parts.

It is important to emphasize the solution of the differential nonlinear Riccati equation (4.9) can be found by solving the nonlinear algebraic equation if $t_f = \infty$. thus, matrix K is found from

$$0 = -Q - A^T K - KA + KBR^{-1}B^T K, \tag{4.12}$$

4.2.1 System States

If the system is linear and time invariant, we are guaranteed that it may be represented in the form of equation (4.1). The state variables $x_1, x_2, \ldots, x_n$ are the components of the state vector x. These state variables are the minimum number of variables containing sufficient information about the past history of the system to allow one to compute the future of the system, assuming the control inputs are known. The state variables are not purely mathematical but have true physical meaning. The system states considered for this study are defined in previous chapter.

4.2.2 Performance Index

The performance of the system is specified in terms of a performance index that is to be minimized by the optimal controller. It is presented in equation (4.2). The components of Q and R are to choose mathematically specifying the way we wish the system to perform. For example in first case, if we let $R = 0$ but require Q to be nonzero, we are saying in effect that there is no charge for the control effort used; but we penalize the state for being nonzero. Hence the best control strategy would be in the form of infinite impulses. This control would drive the state to zero in the shortest possible time with the greatest effort and in second case, If we let $Q = 0$ for nonzero R, then we penalize for control effort but do not charge for the trajectory the state x follows. In this case the best control to use is $u = 0$; i.e., not to provide any control effort at all.

These are two extreme cases, but they emphasize the importance in choosing the components of *Q* and *R*.

$$Q = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & T^2_{12}+1 & 0 & 0 & 0 & -T^2_{12} & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & -T^2_{12} & 0 & 0 & 0 & T^2_{12}+1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$R = I = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

Linear quadratic technique used gives a feedback gain matrix which is an optimal solution for the problem since it minimizes the performance index. Results of two area system when solved using this method are presented in the next chapter.

4.2.3 Optimal Controller

The optimal controller that minimizes the cost of the system in state variable form is a function of the present states of the system weighted by the components of a constant gain matrix K of dimension *m x n*:

$$u = -K_F x. \tag{4.13}$$

This optimal gain matrix K is determined by solving a matrix differential equation, the matrix Riccati equation. For the infinite time problem, the Riccati equation has a steady-state solution. Since the gain matrix is a constant, the optimally controlled system can be expressed in the closed-loop form.

System Conditions – Controllability and Observability

The conditions of controllability and observability must be satisfied by the system for an optimal controller in the feedback form of equation (4.11). A system in the state variable form given by equation (4.1) is said to be controllable when all the state variables are affected by input. Given a set of performance criteria, i.e., settling time, peakovershoot, a matrix K can be found that will allow the closed-loop system to perform in the desired manner. If the system is controllable, it is said that the pair (A, B) is controllable.

Before presenting the concept of observability, we must introduce the matrix D of dimension $p \times n$ where

$$Q \triangleq D' D.$$

We define a new variable Y, a $p \times 1$ vector $p \leq n$, by

$$Y = D x. \tag{4.14}$$

The components of Y are a linear combination of the state variables of the system. The system is said to be observable from Y if, given the information contained in Y, we can construct complete information about the state x. This condition often stated as the pair (A, D) is observable, or identically, the pair (A, Q) is observable.

If the system described in the form of equation (4.1) with performance index given by equation (4.2) is unstable (some eigenvalues of A are in the right-hand complex plane), and the unstable states are observable from the cost then it is necessary that those unstable states be controllable for an optimal controller in the form of equation (4.10) to exist but because of following reasons optimal control is quite often impractical for the implementation.

- The optimal control is a function of all the states of the system. In practice all the states may not be available. The inaccessible states or missing states are required to be estimated.
- It may not be economical to transfer all the information over long distances.
- The control, which is a function of the states in turn, is dependent on the load demand. Accurate prediction of load demand may be essential for realizing optimal controller.
- The optimal control is also dependent on the weighing matrices and is not unique.

Therefore, this control scheme is implemented to two area system with non-reheat turbine without non-linearity while the next proposed controller is applied to all mathematical models developed.

4.3 Fuzzy Logic Controller

Since the pioneer work of Mamdani and his colleagues on fuzzy logic control [126]-[128] motivated by Zadeh's work on fuzzy set theory [129, 130], the study of fuzzy control has been paid growing attention. Fuzzy set theory is an approach to mimic human processes of perception, object recognition, decision making, etc, which has become growing interest to knowledge engineering. The advantage of using fuzzy set theory to construct controllers lie in its ability to merge the experience, heuristics and intuition of expert operators in the controller design. This has led to the applications of fuzzy control, especially in industrial process control, where the expert knowledge plays important role [131].

Fuzzy logic controllers are based on the concepts of fuzzy implication and the compositional rules of inference by which the control action can be obtained from a set of linguistically described knowledge given by experts or experienced operators. Usually the expert knowledge is in the form of control rules, namely the conditional statements "If *states of* *process*, then *control action*". Since the reasoning of the operator or expert is not very precise in the sense of states and control actions involved in the process, the fuzzy sets are considered as labels in the statements. The input variables of a fuzzy logic controller are usually taken in the form of error (e) between set-point and process output, the change rate in error ($\dot{e}$), the integral of error ($\int edt$), etc. the output variable can be in the form of process input (u) or the change rate of process input (u). For the study of load frequency control problem for two and three area interconnected power system, in this work, two inputs one is area control error and another is derivative of area control error and only one output are considered in designing the fuzzy controller.

4.3.1 Normalization of Controller Inputs and Output

A fuzzy logic controller is usually designed so that its inputs are in an appropriate range. However, the real measurements may not fall into the same range. They need to be normalized to the range designed for the controller. For the real measurements of error (e) and rate of change of error ($\dot{e}$), their bounds may not be precisely known. The normalization is realized as follows, choose k_1, k_2 so that k_1e, $k_2\dot{e} \in$ [- D, D] is usually satisfied, the values outside the range are limited. Therefore a saturated nonlinearity is introduced in the first stage. In case of fuzzy controller designed in this work, area control error and rate of change of area control error are in the range given below;

ACE = {-0.002 +0.002}

$\dot{ACE}$ = {-0.003 +0.003}

Similarly, ranges are chosen depending upon the system for which fuzzy controller is designed. Similarly output is also defined over the range [-D, D] similar to the inputs.

4.3.2 Fuzzification

Consider a set of 2N + 1 fuzzy labels F_1, F_2..., F_{2N+1} (F_i may stand for each input defined over a range [-D, D]. Each fuzzy label is also given a linguistic representation like 'positive small'. The central value of a fuzzy label can be defined as the centre of the range where the grade of membership is unity. Let u_j stand for the central value of F_j, we can choose

$$u_j = \frac{j-N-1}{N}D \quad j=1,2,...,2N+1$$

if the set of fuzzy labels is arranged uniformly.

The membership function $\mu F_j(x)$ of each fuzzy label is chosen as:

$$\mu F_j(x)=\begin{cases} unity & if\ x=u_j \\ non-decreasing & if\ x\in(u_{j-1,}u_j) \\ non-increasing & if\ x\in(u_j,u_{j+1}) \\ zero & otherwise \end{cases}$$

To avoid discontinuity (incompleteness), we need a restriction that $\mu F_j(x)+\mu F_{j+1}(x)\neq o,\forall x\in(u_{j,}u_{j+1})$. The shape of membership function may be triangular, trapezoidal, quantized, sinusoidal, or bell shaped, etc. Triangular, trapezoidal and bell shaped membership functions are used for variables and dynamic performance is comprehensively analyzed with different number of membership functions i.e. 3, 5, and 7.

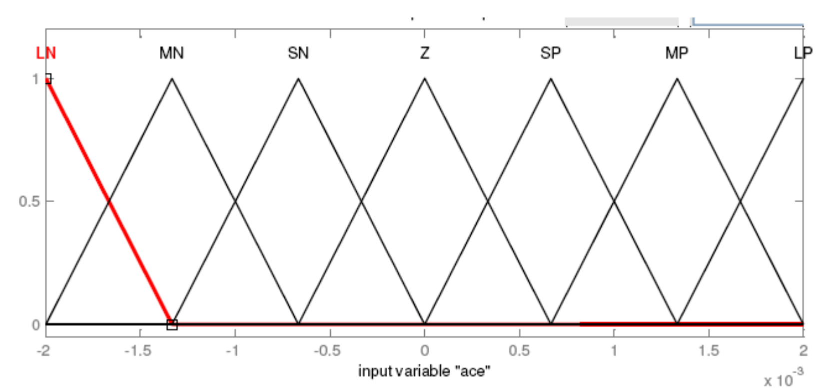

Figure 4.1: Triangular membership function of one variable

4.3.3 Fuzzy Conditional Statements and Fuzzy Control Rules

In an FLC, the dynamic behavior of a fuzzy system is characterized by a set of linguistic description rules based on expert knowledge. The expert knowledge is usually of the form:

IF (a set of conditions is satisfied) THEN (a set of consequences can be inferred)

Since the antecedents and the consequent of these IF-THEN rules are associated with fuzzy concepts (linguistic terms), they are often called fuzzy conditional statements. In our terminology 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, a fuzzy control rule provides a convenient way for expressing control policy and domain knowledge. Furthermore, 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 system, fuzzy control rule have the form:

R_1: if x is A_1 and y is B_1 then z is C_1,

R_2: if x is A_2 and y is B_2 then z is C_2,

… … … …

… … … …

R_n: if x is A_n and y is B_n then z is C_n,

Where x, y, z are linguistic variables representing two process state variables and one control variable, respectively. A_i ; B_i ; C_i are linguistic values of the linguistic variables x, y and z in the universe of discourse U,V, and W, respectively, with i=1,2,…,n. An implicit sentence connective "*also" links* the rules into a rule set or, equivalently, a rule base.

A fuzzy control rule, such as "if (x is A_i and y is B_i) then (z is C_i)" is implemented by

$$\mu_{R_i} \cong \mu_{(A_i \ and \ B_i \rightarrow C_i)}(u,v,w) = [\mu_{A_i}(u) and \mu_{B_i}(v)] \rightarrow \mu_{C_i}(w)$$

fuzzy implication (fuzzy relation) R_i and is defined as follows:

Where A_i and B_i are a fuzzy set A_i x B_i in UxV ;

$$R_i \cong (A_i and B_i) \rightarrow C_i$$

is a fuzzy implication (relation) in UxVxW; and '→' denotes a fuzzy implication function.

surface view of the rules designed for one type of fuzzy control model implemented for two area non reheat turbine system, is shown in figure 4.2 while all rules followed are given in Table 4.1.

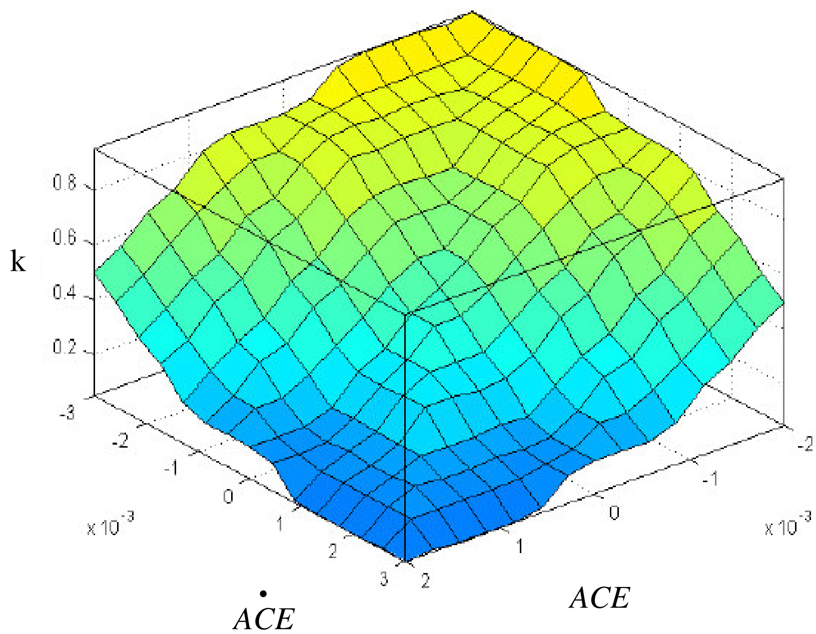

Figure 4.2: Surface view based on rules designed for one type of fuzzy controller

Table 4.1: Fuzzy logic rules for the Integral gain

$\dot{ACE}$

ACE	LN	MN	SN	Z	SP	MP	LP
LN	LP	LP	LP	MP	MP	SP	Z
MN	LP	MP	MP	MP	SP	ZE	SN
SN	LP	MP	SP	SP	Z	SN	MN
Z	MP	MP	SP	Z	SN	MN	MN
SP	MP	SP	Z	SN	SN	MN	LN
MP	SP	Z	SN	MN	MN	MN	LN
LP	Z	SN	MN	MN	LN	LN	LN

LN: large negative, MN: medium negative, SN: small negative, Z: zero, SP: small positive, MP: medium positive and LP: large positive

4.3.4 Defuzzification

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:

$$z_o = \text{defuzzifier}(z)$$

Where z_o is the non-fuzzy control output and defuzzifier is the defuzzification operator. Bisector of area is chosen as the defuzzification method for all simulation purposes in this study. The bisector is the vertical line that will divide the region into two sub-regions of equal area. It is sometimes, but not always coincident with the centroid line. Crisp value of integral gain with this defuzzification technique gives better results in terms of improved dynamic response.

4.3.5 Steps in Designing of Proposed Fuzzy Controller for Multi-area LFC

Step 1: -First step is to determine the input variables and determine the degree to which they belong to each of the appropriate fuzzy sets in a membership function. The inputs are always a crisp numerical valve limited to the universe of discourse of the input variable and the output is a fuzzy degree of membership in the qualifying linguistic set. For our study we have the ACE and rate of change of ACE of each area as the input variable between the range -0.002 to +0.002, 7 Membership function were defined for each input.

Step 2: - Once the inputs have been fuzzified we know the degree to which each part of the antecedent has been satisfied for each rule. If the antecedent of a given rule has more than one part, the fuzzy operator is applied to obtain one number that represents the result of the antecedent for that rule. This number will then be applied to the output function. For the study "OR' operator supported by 'Maximum' and 'Probabilistic' method that is known as the algebraic sum are applied while framing the rules. Totally 49 rules were framed for the study.

Step 3: - Every rule has a weight (a number between 0 and 1) that is applied to the number given by the antecedent. Generally this weight is 1, so it has no effect at all on the implication process.

Step 4: -Aggregation is the process by which fuzzy sets that represents the output of each rule are combined into a single fuzzy set. The input of the aggregation process is the list of the truncated output function returned by the implication process for each rule. The three methods used for study are (a) Maximum, (b) Probabilistic and (c) Sum.

Step 5: -The final desired output each variable is generally a simple number. However the aggregate of a fuzzy set encompasses a range of output value, which is defuzzified in order to resolve a single output valve from the set.

It is observed that fuzzy implications as well as fuzzy sets are very suitable to describe the process of human thinking where ill-defined and linguistic concepts of terms are usually treated. This is because fuzzy propositions in fuzzy implications are qualitative rather than quantitative. However, it is not sufficient for control to express a situation or a protocol qualitatively. We have to execute a qualitative idea in a real situation. Fuzzy sets are also suitable for this aim, since they have quantitative semantics as well, expressed by membership functions. Thus the execution of a set of fuzzy control rules is numerically performed by a method of fuzzy reasoning where the aggregation of the outputs inferred from various control rules is also nicely performed.

There are some important features of fuzzy control which are not usually mentioned but should be stressed. By fuzzy control we can easily realize a controller working under multiple objectives such as safety, energy saving, stable operation, etc. this is accomplished by setting some control rules under one criterion and others under different criterion. The coordination of different objectives is well performed by fuzzy reasoning. There are many variables which can not be physically measured but useful to control and thus are actually noted by an experienced operator. Those variables have not been used in ordinary control, because of unmeasurability and lack of a method of utilization.

Robustness may seem to be another advantage of fuzzy control. However, we can not expect that robustness is automatically realized by fuzzy control without introducing a specific structure for the purpose. It seems that simple adaptive logic is necessary to realize robustness. It is strongly desirable to introduce fuzzy control into analysis of dynamic parameters in load frequency control of interconnected power system by taking advantage of these features. Fortunately, in recent years, demand for fuzzy control in industry has grown, as people have got to know about taking advantage of uncertain information and express vague ideas by using fuzzy logic.

4.4 Summary

This chapter presents the details of the control strategies which are implemented in the thesis. This comprehensively discusses linear quadratic regulator technique and its limitations. Fuzzy logic based integral controller is the next control scheme proposed for solution of load frequency control problem of multi-area power system in this work. All aspects of designing of fuzzy logic controller are also presented. Next chapter consists of simulation results of two area system with different system conditions on implementation of proposed controllers.