CHAPTER 4

FREQUENCY STABILIZATION USING FUZZY LOGIC CONTROLLER

4.1 INTRODUCTION

Problems in the real world quite often turn out to be complex owing to an element of uncertainty either in the parameters which define the problem or in the situations in which the problem occurs.

The uncertainty may arise due to partial information about the problem, or due to information which is not fully reliable, or due to inherent imprecision in the language with which the problem is defined, or due to receipt of information from more than one source about the problem which is conflicting (Ross 2000, John Yen et al 1999). It is in such situations the fuzzy set theory exhibits immense potential for effective solving of the uncertainties in the problem. Fuzziness means ‘vagueness’. Fuzzy set theory is an excellent mathematical tool to handle the uncertainty arising due to vagueness.

The fuzzy logic provides a strong framework for achieving robust and simple solutions among different approaches of intelligent computation. Fuzzy model is collection of IF - THEN rules with vague predicates that use a fuzzy reasoning such as Sugeno and Mamdani models. Sugeno type systems can be used to model any inference system in which the output membership functions are either linear or constant whereas Mamdani type produces either linear or nonlinear output. The fuzzy logic controller consists of four stages;
fuzzification of inputs, derivation of rules based on knowledge, inference mechanism and defuzzification.

Fuzzy logic system is universal function approximation. In general, the goal of the fuzzy logic system is to yield a set of outputs for given inputs in a non-linear system, without using any mathematical model, but by using linguistic rules.

It has many advantages and they are:

- Fuzzy logic is conceptually easy to understand. The mathematical concepts behind fuzzy reasoning are very simple. What makes fuzzy better is the "Naturalness" of its approach and not its far-reaching complexity.

- Fuzzy logic is flexible. With any given system, it is easy to manipulate it or layer more functionality on top of it without starting again from scratch.

- Fuzzy logic is tolerant of imprecise data. Everything is imprecise if it is looked closely enough, but more than that, most things are imprecise even on careful inspection. Fuzzy reasoning builds this understanding into the process rather than tackling it onto the end.

- Fuzzy logic can model nonlinear functions of arbitrary complexity. One can create a fuzzy system to match any set of input-output data. This process is made particularly easy by online tuning techniques like Supervisory Expert Fuzzy Controller (SEFC), which are available in the Fuzzy Logic Toolbox.
• Fuzzy logic can be built on top of the experience of experts. In direct contrast to neural networks, which take training data and generate opaque, impenetrable models, fuzzy logic lets one to rely on the experience of people who already understand one’s system.

• Fuzzy logic can be blended with conventional control techniques. Fuzzy systems don’t necessarily replace conventional control methods. In many cases fuzzy systems augment them and simplify their implementation.

• Fuzzy logic is based on natural language. The basis for fuzzy logic is the basis for human communication. This observation underpins many of the other statements about fuzzy logic.

4.2 FUZZY SET THEORY

The concept of fuzzy set theory was introduced by Zadeh (1965). He states, “Much of the decision making in the real world takes place in an environment in which the goals, the constraints and the consequences of possible actions are not known precisely”. In the recent years, fuzzy set theory applications have received increasing attention in designing intelligent controllers for complex industrial processes. We live in a world of marvelous complexity and variety where events never repeat exactly. Real world solutions are very often not crisp; but are vague, uncertain, and imprecise. Fuzzy logic provides us not only with meaningful and powerful representation for measurement of uncertainties but also with a meaningful representation of vague concepts in natural language. The closer one looks at a real world problem, the fuzzier becomes its solution. Fuzzy systems can focus on modeling problem characterized by imprecise or ambiguous information. The underlying power of fuzzy set theory is that it uses linguistic variables rather
than quantitative variables to represent imprecise concepts (Haack 1979, Dombi 1990). The incorporation of fuzzy set theory and fuzzy logic into computer models has shown tremendous pay off in areas where intuition and judgment still play major role in the model.

Fuzziness describes the ambiguity of an event whereas randomness describes the uncertainty in the occurrence of the event. In the modern view, uncertainty is considered essential to science, it is not only an unavoidable plague, but it has in fact a great utility. A fuzzy set can be defined mathematically by assigning to each possible individual, in the universe of discourse, a value representing its grade of membership in the fuzzy set.

4.3 FUZZY SET OPERATIONS

The basic three fuzzy set operations are union ($\cup$), intersection ($\cap$) and complement ($\neg$). The fuzzy logic method uses fuzzy equivalents of logical AND, OR and NOT operations to build up fuzzy logic rules (Jang et al 2004). In conventional set theory, AND is said to be the intersection of the sets and OR the union. The fuzzy operators based on values between zero and one, are sometimes said to be true generalizations of the Boolean operators.

Let x and y be two fuzzy sets on the universe X and Y, it denotes their membership function by $\mu_x$ and $\mu_y$. Then the standard fuzzy AND ($\cap$) is defined as the minimum of $\mu_x$ and $\mu_y$, the degree of truth of ($x \in X$) AND ($y \in Y$) is $\min \{\mu_x (x), \mu_y (y)\}$. The standard fuzzy OR ($\cup$) operator is typically defined as the maximum value of $\mu_x$ and $\mu_y$, the degree of truth of ($x \in X$) OR ($y \in Y$) is $\max \{\mu_x (x), \mu_y (y)\}$. For membership $\mu_x$ and $\mu_y$ the fuzzy NOT (complement) operation is defined by $\overline{\mu}_x = 1 - \mu_x$ and $\overline{\mu}_y = 1 - \mu_y$. 
In general, the logical operations (intersection, union and complement) on sets A and B are defined as

For fuzzy set A, \( A = \{(x, \mu_A(x)) / x \in X\} \).

For fuzzy set B, \( B = \{(x, \mu_B(x)) / x \in X\} \).

Intersection, \( \mu_A(x \cap B(x)) = \mu_A(x \cap B(x)) = \min \{\mu_A(x), \mu_B(x)\} \)

Union, \( \mu_A(x \cup B(x)) = \mu_A(x \cup B(x)) = \max \{\mu_A(x), \mu_B(x)\} \)

Complement, \( \bar{\mu}_A(x) = 1 - \mu_A(x) \)

(4.1)

4.4 MEMBERSHIP FUNCTIONS

The membership functions play an important role in designing fuzzy systems (Passino et al. 1998). The membership functions characterize the fuzziness in a fuzzy set whether the elements in the set are discrete or continuous in a graphical form for eventual use in mathematical formalism of fuzzy set theory. The shape of membership function describes the fuzziness in graphical form. The shape of membership functions is also important in the development of fuzzy system.

The membership functions can be symmetrical or asymmetrical. A uniform representation of membership functions is desirable (Hiyama 1997). The membership function defines how each point in the input space is mapped to a membership value in the interval \([0, 1]\).

4.5 MAMDANI FUZZY LOGIC INFERENCE SYSTEM

Mamdani-type of fuzzy logic controller contains four main parts, two of which perform transformations shown in the Figure 4.1. The four parts are:
4.5.1 Fuzzifier

The fuzzifier performs measurement of the input variables (input signals, real variables), scale mapping and fuzzification (transformation 1). Thus all the monitoring input signals are scaled and the measured signals (crisp input quantities which have numerical values) are transformed into fuzzy quantities by the process of fuzzification. This transformation is performed by using membership functions. In a conventional fuzzy logic controller, the number of membership functions and the shapes of these are initially determined by the user. A membership function has a value between 0 and 1, and it indicates the degree of belongingness of a quantity to a fuzzy set. If it is absolutely certain that the quantity belongs to the fuzzy set, then its value is 1 (it is 100% certain that the quantity belongs to this set), but if it is absolutely certain that it does not belong to this set then its value is 0.
Similarly if the quantity belongs to the fuzzy set to an extent of 50%, then the membership function is 0.5.

There are many types of different membership functions, piecewise linear or continuous. The commonly used membership functions are bell-shaped, sigmoid, gaussian, triangular, and trapezoidal. The choice of the type of membership function used in a specific problem is not unique. Thus, it is reasonable to specify parameterized membership functions, which can be fitted to a practical problem (Chia-Feng 2004). If the number of elements in the universe $X$ is very large or if a continuum is used for $X$ then it is useful to have a parameterized membership function, where the parameters are adjusted according to the given problem. Parameterized membership functions play an important role in adaptive fuzzy systems, but are also useful for digital implementation (Talaq 1999). Due to their simple forms and high computational efficiency, simple membership functions, which contain straight line segments, are used extensively in various implementations. Obviously, the triangular membership function is a special case of the trapezoidal one. Triangular membership function depends on three parameters $a$, $b$, $c$ and can be described as follows by considering four regions.

$$
\mu_A(x; a, b, c) = \begin{cases} 
0, & \text{if } x < a \\
(x-a) / (b-a), & \text{if } a \leq x \leq b \\
(c-x) / (c-b), & \text{if } b \leq x \leq c \\
0, & \text{if } x > c
\end{cases}
$$

(4.2)

Figure 4.2 Triangular Membership Function
A triangular membership function, shown in Figure 4.2, is used for both the input and output variables and the points a, b, c are also denoted. Alternatively, it is possible to give a more compact form as given below in Equation (4.3),

$$\mu_A(x; a, b, c) = \max \left\{ \min \left\{ \frac{x-a}{b-a}, \frac{c-x}{c-b} \right\}, 0 \right\}$$  (4.3)

### 4.5.2 Knowledge Base

The knowledge base consists of the data base and the linguistic control rule base. The data base provides the information which is used to define the linguistic control rules and the fuzzy data manipulation in the fuzzy logic controller. The rule base contains a set of if-then rules and these rules specify the control goal actions by means of a set of linguistic control rules. In other words, the rule base contains rules which would be provided by an expert.

The fuzzy logic controller looks at the input signals and by using the expert rules determines the appropriate output signals (control actions). The main methods of developing a rule base are:

- Using the experience and knowledge of an expert for the application and the control goals
- Modeling the control action of the operator
- Modeling the process
- Using a self-organized fuzzy controller
- Using artificial neural networks
When the initial rules are obtained by using expert which is related to physical considerations, these can be formed by considering that the three main objectives to be achieved by the fuzzy logic controller are:

- Removal of any significant errors in the process output by suitable adjustment of the control output
- Ensuring a smooth control action near the reference value (small oscillations in the process output are not transmitted to the control input)
- Preventing the process output exceeding user specified values

By considering the two dimensional matrix of the input variables, each subspace is associated with a fuzzy output situation.

### 4.5.3 Inference Engine

It is the kernel of a fuzzy logic controller and has the capability of both simulating human decision-making based on fuzzy concepts and of inferring fuzzy control actions by using fuzzy implication and fuzzy logic rules of inference as shown in Figure 4.3. In other words, once all the monitored input variables are transformed into their respective linguistic variables, the inference engine evaluates the set of if-then rules and thus result is obtained which is again a linguistic value for the linguistic variable. This linguistic result has to be then transformed into a crisp output value of the fuzzy logic control.
4.5.4 Defuzzifier

The second transformation is performed by the defuzzifier which performs scale mapping as well as defuzzification. The defuzzifier yields a non-fuzzy, crisp control action from the inferred fuzzy control action by using the consequent membership functions of the rules. There are many defuzzification techniques. They are centre of gravity method, height method, mean of maxima method, first of maxima method, sum of maxima, centre of average etc.

4.6 FUZZY RULE BASED FREQUENCY STABILIZATION IN A PARALLEL AC-DC INTERCONNECTED POWER SYSTEM

4.6.1 Controller Design

Fuzzy control is increasingly used to solve the control problems in areas where system complexity, development time and cost are the critical issues. Fuzzy logic is a powerful tool for developing control algorithm in all type of applications and provides better results than the classical control method.

![Graphical Interpretation of Fuzzification, Inference](image.png)

**Figure 4.3** Graphical Interpretation of Fuzzification, Inference
The fuzzy logic controller is very effective in suppressing the frequency oscillations caused by rapid load disturbances in an interconnected power system. In order to maintain the frequency in the interconnected AC-DC power system, one can design the fuzzy logic controller. The structure of typical closed loop fuzzy logic control scheme for interconnected power system is shown in Figure 4.4.

![Figure 4.4 Structure of the Fuzzy Logic Controller for Interconnected Power System](image)

In the proposed fuzzy logic system, for the stabilization of frequency in a parallel AC–DC interconnected power systems, the Error (E) change in Error (ΔE) are considered as the two inputs and the output (U) is applied to the plant to get the desired output.

### 4.6.2 Membership Functions and Rule-Base

The method of fuzzification has found increasing application in power systems. In this Fuzzy Logic Controller (FLC), membership function (MF) specifies the degree to which a given input belongs to a set. In the case of FLC, seven membership functions in triangular shape have been chosen for the inputs of Error (E), change in Error (ΔE) and output (U). The input range for the E, ΔE and control output (U) are normalized based on the load
disturbance from the normal operation. The linguistic descriptions of input membership functions are Negative Large (NL), Negative Medium (NM), Negative Small (NS), Zero (ZE), Positive Small (PS), Positive Medium (PM) and Positive Large (PL). The output membership functions are Zero (ZE), Very Small (VS), Small (S), Medium (M), Large (L), Very Large (VL) and Very Very Large (VVL). The fuzzy membership functions for inputs and outputs are shown in Figures 4.5 and 4.6. The minimum operation has been selected for the fuzzy implication. For the two-input fuzzy system, it is generally expressed as,

$$\mu_{A_i}(x_1 \cap \bar{A}_i(x_2)) \min \left\{ \mu_{A_i}(x_1), \mu_{A_i}(x_2) \right\}$$

(4.4)

where $A_i(x_1)$ and $A_i(x_2)$ are input fuzzy sets. The rule base of the fuzzy controller relates the inputs (E and $\Delta E$) to output (U). Practically the load on the power system is time variant. The power demand is increased during peak load period and reduced during light load period. Whenever the power demand is increased, the frequency of the system will come down. Similarly whenever the power demand is reduced, the frequency of the system will increase. To stabilize the system frequency around the set value, the controller output has to be modified accordingly. For example the frequency of the system is below the set value which causes positive error. In this situation the controller has to increase its output to bring the system frequency to the set level. Using such a fundamental knowledge the rule base for the proposed controller has been developed; further the rules are fine tuned to obtain better performance. The rule base of the proposed system is given in Table 4.1. The structure of the control rules of the fuzzy controller with two inputs and one output is expressed as,

If (E is PL and $\Delta E$ is PL) then control signal U is VVL.       (4.5)
Figure 4.5 Input membership functions of fuzzy controller

(a) Error (E)

(b) Change in Error (ΔE)
The relationship between inputs and output of the fuzzy rules are shown in Figure 4.7 as a three dimensional surface view. The fuzzy rule viewer for the given typical values of both inputs and output is shown in Figure 4.8. It is interesting to see that there will be a non-linear relationship between the inputs and the output.
4.6.3 Defuzzification Method

The result of the fuzzy inference is a fuzzy output set. On the other hand, every control task will imply the existence of crisp value at the fuzzy controller output. The procedure which extracts crisp output value from a fuzzy output set is called defuzzification. There are various types of
defuzzification. However, the centre-average defuzzification method is most frequently used to calculate the crisp output and is expressed as

$$U^{Crisp} = \frac{\sum_{i=1}^{n} c_i \mu(c_i)}{\sum_{i=1}^{n} \mu(c_i)}$$

(4.6)

where $U^{Crisp}$ is the output of the fuzzy controller, $c_i$ denotes the centre of the membership function of the consequent $i^{th}$ rule, $\mu$ denotes the membership value for the rule’s premise and $n$ represents the total number of fuzzy rules.

### 4.6.4 Results and Discussions

In this research, a three area reheat interconnected AC-DC thermal power system has been considered for the system study. It is shown in Figure 4.9. The simulation tests were carried out to compare system dynamic response under similar conditions of operation of the power system.

For the system study, conventional integral control and the fuzzy control scheme have been applied for a three area interconnected AC-DC power system. The three area thermal power system data are given in the appendix. The system study is carried out by the MAT LAB software. The system is simulated for a step load disturbance of 10% (0.1 p.u. MW) occurring in area-1. Due to this, change in dynamics response of the system has been observed. Figures 4.10, 4.11 and 4.12 indicate the frequency deviations of area 1, 2, and 3 for a 10% step load disturbance in area-1.
Figure 4.9 Modelling of three area interconnected AC-DC reheat thermal power systems using FLC

From system study, frequency deviation in area-1 for a 10% disturbance in area-1 is shown in Figure 4.10. (i) For Integral control, there is an overshoot and the frequency stabilizes after 10 seconds. (ii) For Fuzzy Logic Control, overshoot is eliminated and the frequency stabilizes after 7 seconds.

Figure 4.11 shows the frequency deviation in area-2 for a 10% disturbance in area-1. (i) For Integral control, there is an overshoot and the frequency stabilizes after 11.4 seconds. (ii) For Fuzzy Logic Control, overshoot is eliminated and the frequency stabilizes after in 7.6 seconds. Figure 4.12 shows the frequency deviation in area-3, for a 10% disturbance in area-1. (i) For Integral control, there is an overshoot and the frequency
stabilizes after 11.2 seconds. (ii) For Fuzzy Logic Control, overshoot is eliminated and the frequency stabilizes after in 6.5 seconds. Also the same study is done in the system’s response for a step-load disturbance of 30 %(0.3 p.u.MW) occurring in area-1 and the frequency deviations of area 1, 2, and 3 are shown in Figures 4.13, 4.14 and 4.15 respectively. From the comparison, one can observe that the fuzzy logic controller instantly responds to the step load disturbance and makes the system to stabilize within a reasonable time.

Figure 4.10 Frequency deviations in area-1 for a 10% Disturbance in area-1
Figure 4.11 Frequency deviations in area-2 for a 10% Disturbance in area-1

Figure 4.12 Frequency deviations in area-3 for a 10% Disturbance in area-1
Figure 4.13 Frequency deviations in area-1 for a 30% Disturbance in area-1

Figure 4.14 Frequency deviations in area-2 for a 30% Disturbance in area-1
Figure 4.15 Frequency deviations in area-3 for a 30\% Disturbance in area-1

The performance by numerical comparison for a step load disturbance of 10\% and 30\% in area-1 are presented in Table 4.2. From this table, one can observe that the settling time in FLC is faster than the integral controller.

Table 4.2 Numerical comparison for a step load disturbance

<table>
<thead>
<tr>
<th>Types of Control</th>
<th>Area</th>
<th>Settling Time $T_s$ (S)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>10% Disturbance</td>
</tr>
<tr>
<td>Integral Control</td>
<td>Area-1</td>
<td>10.8</td>
</tr>
<tr>
<td></td>
<td>Area-2</td>
<td>10.4</td>
</tr>
<tr>
<td></td>
<td>Area-3</td>
<td>10.3</td>
</tr>
<tr>
<td>Fuzzy Control</td>
<td>Area-1</td>
<td>5.8</td>
</tr>
<tr>
<td></td>
<td>Area-2</td>
<td>5.7</td>
</tr>
<tr>
<td></td>
<td>Area-3</td>
<td>5.5</td>
</tr>
</tbody>
</table>
The Area Control Error (ACE) for a 10% step load disturbance in area-1 is shown in Figures 4.16, 4.17 and 4.18. From the comparison, one can observe that the fuzzy logic controller instantly responds to the step load disturbance and attains the steady state faster than the integral controller.

Figure 4.16 ACE deviations in area-1 (10% Disturbance in Area-1)

Figure 4.17 ACE deviations in area-2 (10% Disturbance in Area-1)
Similarly, the Area Control Error (ACE) for a 30% step load disturbance in area-1 is shown in Figures 4.19, 4.20 and 4.21. From the comparison, one can observe that the fuzzy logic controller instantly responds to the step load disturbance and reduces the system error within a short time than the integral controller.
Figure 4.20 ACE deviations in area-2 (30% Disturbance in Area-1)

Figure 4.21 ACE deviations in area-3 (30% Disturbance in Area-1)
4.7 SUMMARY

i. The stabilization of frequency deviation in an interconnected AC-DC thermal power systems were simulated using fuzzy logic controller.

ii. The fuzzy logic control scheme has been designed and implemented in an easier and quicker way than a classical integral control method.

iii. The stabilization of frequency deviation has been studied through simulation using Fuzzy logic system with 49 rules and seven membership functions for each variable. The Mamdani fuzzy inference system is adapted for simulation. Triangular membership function is used for both inputs as well as output. In fuzzy logic based system, the actions of a human expert are clearly present in the rule base.

iv. Simulation results revealed that the fuzzy logic controller performance was better for stabilizing the frequency deviation under different disturbance conditions and also reduce the system error within a short time than the integral controller.

v. The system response follows the controller output and reaches the steady state within a reasonable time period.