CHAPTER 5

FUZZY LOGIC CONTROLLER FOR HEAVY DUTY
GAS TURBINE PLANTS

The importance, feasibility and simplicity of soft computing controllers are explained in chapter 4. In this thesis, two soft computing controllers like Fuzzy Logic and Artificial Neural Networks have been taken for investigation. The ANN controller has been developed in chapter 4 and it is not found to be the appropriate choice for controlling heavy duty gas turbine plant. Hence an attempt is made to control the gas plant using Fuzzy Logic because of its human knowledge, inference and decision making capability.

Like ANN controller, Fuzzy Logic Controller (FLC) is also in need of the simplified transfer function model of the heavy duty gas turbine plant. The simplified transfer function model consists of droop governor, valve positioner, fuel system, turbine and rotor. The transfer function model and its governing equations for the development of FLC have been presented in chapter 2.

In this chapter, The Fuzzy Logic Controller has been developed using both Sugeno and Mamdani models. In both the models, error and change in error in speed have been considered as input to the FLC. The output of the FLC controls the fuel input to the turbine.
In both the models, the inputs are divided into seven linguistic variables. The membership functions are symmetrical and triangular shaped. Since the two inputs have seven membership functions each, the total number of rules will be forty nine. The rules are developed by analyzing the performance of the PID controller.

As far as output is concerned, the Mamdani model has seven linguistic variable of symmetrical and triangular shaped. The output membership functions are constants in Sugeno model. The range for the membership functions are selected appropriately. Centre of gravity and weighted average method can be used for defuzzification in Mamdani and Sugeno model respectively. The PID controller is to be replaced by means of FLC. The system is then simulated using both Mamdani and Sugeno model. The optimum response can be achieved using FLC.

5.1 Fuzzy Logic

The concept of fuzzy set theory was introduced by Zadeh (1965) and it was introduced in 1979 for solving power system problems as explained by Bansal (2003), Momoh (1995), Song (1997) and Tomsovic (2000). The generalization of classical set theory provides Fuzzy set theory. In classical set, an element of the universe either belongs to or does not belong to the set. The degree of association of an element is crisp in case of classical set. In Fuzzy set the degree of association of an element is continuously varying. Membership function is used to obtain the continuous varying degree of association. Depending upon the requirements and constrains of the problem, the membership function is designed. Fuzzy logic implements knowledge base of the human via rules.
Due to the use of fuzzy variables, the system can be easily understandable to a non expert operator.

The main advantages of Fuzzy set theory over conventional methods are

- Conceptually easy to understand
- Tolerant to imprecise data
- Capability to handle ambiguity expressed in diagnostic process.
- Develops control as a fuzzy relation between informations about the conditions of the process, which has to be controlled.

5.2 FUZZY LOGIC CONTROL

Fuzzy logic, which is the logic on which fuzzy control is based, is much closer in spirit to human thinking and natural language than the traditional logic system. The Fuzzy Logic Controller is a set of linguistic control rules related by the dual concepts of fuzzy implication and the compositional rule of inference. Fuzzy Logic Controller provides an algorithm which can convert the linguistic control strategy based on expert knowledge into an automatic control strategy. FLC yields results superior to those obtained using conventional techniques.

The FLC comprises of four principle components:

- Fuzzification interface,
- Knowledge base,
- Decision making logic, and
- Defuzzification interface.
The fuzzification interface involves the measurement of values of input variables, scale mapping that transfers the range of values of input variables into corresponding universes of discourse and performs the function of fuzzification that converts the input data into suitable linguistic values which may be viewed as labels of fuzzy sets. The fuzzified inputs and rules which are developed using knowledge base are used by the decision making logic and yields the output. The output is of fuzzy value, which cannot be understand by the process. The fuzzy value is then converted into crisp value using defuzzification. The Basic configuration of FLC given by Chuen Chien Lee is shown in Figure 5.1.

![Figure 5.1 Basic Configuration of fuzzy logic control.](image)

5.2.1 **Mamdani model**

There are two principle approaches to the derivation of fuzzy control rules. The first is a heuristic method in which a collection of fuzzy
rules is formed by analyzing the behaviour of a controlled process. The control rules are derived in such a way that the deviation from a desired state can be corrected and the control objective can be achieved. The derivation is purely heuristic in nature and relies on the qualitative knowledge of process behavior. Several methods of adjustment of rule have been studied. Mamdani (1974)(1975)(1976) proposed a prescriptive algorithm for deriving the best control rules. The Mamdani fuzzy inference system obtained from MATLAB user manual has been shown in Figure 5.2. First the inputs are fuzzified using the membership functions. Then fuzzy operation and implication are applied using the rules. Finally, the fuzzy value has been converted to crisp value using centroid method.

Figure 5.2 Mamdani fuzzy inference system
5.2.2 Sugeno model

The second approach is basically a deterministic method, which can systematically determine the linguistic structure and parameters of the fuzzy control rules that satisfy the control objectives and constraints. Sugeno (1983)(1985) (1988) has successfully applied this method to the design of an FLC. His method provides more systematic approach to the design of FLC and the experimental results are quite remarkable. The Sugeno fuzzy interface provided in MATLAB user manual is shown in Figure 5.3. In this model too the inputs crisp values are converted to fuzzy value with respective linguistic variables using the shape and range of the membership function. Later, using the rules the fuzzy operation and implication are applied. Finally the weighted average method has been used for defuzzification. Since the output membership functions are constants, the weighted average method is adopted.

![Figure 5.3 Sugeno fuzzy inference system](image)

Figure 5.3 Sugeno fuzzy inference system
5.3 FLC FOR HEAVY DUTY GAS TURBINE PLANTS

The FLC has been developed to control heavy duty gas turbine plants using both Mamdani and Sugeno models as explained in section 5.2. Both the models have four stages as explained in section 5.1.

5.3.1 Fuzzy inputs and output

In both the models, there are two inputs and one output. The inputs to the Fuzzy Logic Controller are error (e) in speed and change in error (Δe) in speed. The single output (Δu) is to control the fuel demand. For fuzzification ie. to convert the measured crisp input values into suitable fuzzy value, seven linguistic variables are considered for each inputs. They are NB (Negative Big), NM (Negative Medium), NS (Negative Small), Z (Zero), PS (Positive Small), PM (Positive Medium) and PB (Positive Big). The Membership functions of these subsets are triangular shaped and symmetrical as shown in Figure 5.4. The range for the membership function for error input is from -1.0 to 1.0, for change in error is -3.0 to 3.0 and for output is from -3.5 to 3.5 with a normalization of 0.5. The membership function shown in Figure 5.4 is not only applicable for Mamdani model but also for the Sugeno model. The output membership function for Sugeno model is considered as constant and is shown in Figure 5.5

![Figure 5.4 Membership function for error input](image-url)
Figure 5.5 Output membership function for Sugeno model

5.3.2 Rules

Totally 49 rules have to be developed since there are two inputs with 7 linguistic variables. The rules are framed in order to bring the decision making and inference knowledge of human into fuzzy. Based on the past experience of manual tuning of a controller and analyzing the performance of the PID controller, the rule table is formed. Thus the fuzzy rule table shown in Table 5.1 is constructed with 49 rules. These rules are used to relate the input signal to the output control signal. These decision rules, which are summarized by a fuzzy relation matrix using membership functions, form the basis of the fuzzy logic operation performed by the fuzzy controller. The rule surface shown in Figure 5.6 clearly shows the smooth variation in the output for small variation in the inputs. This will provide smooth control action for the system over the wide range.

Table 5.1 Fuzzy rules

<table>
<thead>
<tr>
<th>Change in error ($\Delta e$)</th>
<th>Error ($e$)</th>
<th>NB</th>
<th>NM</th>
<th>NS</th>
<th>Z</th>
<th>PS</th>
<th>PM</th>
<th>PB</th>
</tr>
</thead>
<tbody>
<tr>
<td>NB</td>
<td>NB</td>
<td>NB</td>
<td>NB</td>
<td>NB</td>
<td>NM</td>
<td>NM</td>
<td>NS</td>
<td>Z</td>
</tr>
<tr>
<td>NM</td>
<td>NB</td>
<td>NB</td>
<td>NB</td>
<td>NB</td>
<td>NM</td>
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<td>NS</td>
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<tr>
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<td>NB</td>
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<td>NS</td>
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<td>Z</td>
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<tr>
<td>Z</td>
<td>NM</td>
<td>NM</td>
<td>NS</td>
<td>NS</td>
<td>Z</td>
<td>PS</td>
<td>PM</td>
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<td>PS</td>
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<td>PM</td>
<td>PM</td>
<td>PB</td>
<td>PB</td>
<td>PB</td>
<td></td>
</tr>
</tbody>
</table>
For example rule 1 in Table 5.1 is:

IF e is NB AND Δe is NB THEN output is NB

![Figure 5.6 Rule surface](image)

5.3.3 Defuzzification

The fuzzy rules are applied and implicated for the fuzzified inputs. Once the controller output is computed after implication, it will be in the form of fuzzy set and cannot be understood by the system. So, defuzzification method has been adopted to convert fuzzy output to crisp value. The centre of gravity method is employed for determining the controller output signal from these membership values for Mamdani model. In Sugeno model, the output will be in the form of constant membership function so, weighted average method is employed to obtain the controller output signal from the membership values.

5.4 FUZZY CONTROLLER PERFORMANCE

As explained in section 5.3, the Fuzzy Logic Controller has been developed using MATLAB Fuzzy logic toolbox in FIS environment. Both
Mamdani and sugeno models have been developed using Fuzzy Toolbox. The transfer function model of heavy duty gas turbine plant explained in chapter 2 has been developed in MATLAB Simulink environment replacing PID controller with FLC. The Fuzzy logic controller developed using Fuzzy Logic Toolbox in FIS environment has been embedded in the Simulink file. The simulation is then carried out for unit step load disturbance.

The response of gas turbine plant with Mamdani fuzzy controller is probed and compared with the response of GA tuned PID controller as shown in Figure 5.7. It is found that FLC provides better control action than GA tuned PID controller. The Sugeno Fuzzy Controller response is then compared with the Mamdani Fuzzy Controller as shown in Figure 5.8. It is found that both the models yield the same response, however, the Sugeno model can be used for developing ANFIS controller using the data collected for ANN controller.

Figure 5.7 Comparison of gas turbine plant with genetic tuned PID controller and Mamdani fuzzy controller
Figure 5.8 Comparison of gas turbine plant with Mamdani FLC and Sugeno FLC

5.5 OPTIMAL FUZZY CONTROLLER

The response of heavy duty gas turbine plant with Mamdani and Sugeno models are tabulated and given in Table 5.2.

Table 5.2 Response of gas turbine plant with PID controller and FLC

<table>
<thead>
<tr>
<th>Controller</th>
<th>Peak Over Shoot (p.u.)</th>
<th>Settling Time (sec)</th>
<th>Steady State Error (p.u.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PID tuned using Genetic Algorithm</td>
<td>1.04</td>
<td>2.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Fuzzy Logic Controller</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mamdani Model</td>
<td>---</td>
<td>2.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Sugeno Model</td>
<td>---</td>
<td>2.0</td>
<td>0.0</td>
</tr>
</tbody>
</table>
From the Table 5.2 it is clear that both Mamdani and Sugeno models produce same type of response. It also shows that both Mamdani and Sugeno models remove the steady state error at less time. The response is much faster and smooth. The peak overshoot has been completely removed. When comparing with other controllers like ZN tuned PID controller, Performance Index tuned PID controller, GA tuned PID controller and ANN controller, FLC provides better optimal response with no overshoot, no steady state error and with less settling time. Fuzzy Logic Controller is thus found to be the optimal controller for heavy duty gas turbine plants.