PROFESSIONAL STUDY OF SOFC WITH FUZZY
LOGIC CONTROLLER FOR ISOLATED OPERATION

4.1 INTRODUCTION

During the past several years, fuzzy control has emerged as one of the most active and fruitful area for research in the applications of fuzzy set theory. 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 logical systems. It provides an effective means of capturing the approximate, inexact nature of the real world [118]. The literature in fuzzy control has been growing rapidly in recent years, for the wide range of engineering applications that have been made. Fuzzy logic controllers are increasingly employed for a wide range of applications in electric power system and they yield results superior to those obtained by conventional control algorithms. Being highly complex and nonlinear, power systems are very difficult to control with conventional methods and linearization techniques. They, very often fail to produce a model that has the actual characteristics of the system [119]. Artificial intelligence based techniques such as fuzzy logic control can overcome these difficulties.

The use of Fuzzy Logic for solving control problems has tremendously increased in various power system control applications. Some of the control applications are in generating unit control (such as excitation control, power system stabilizers etc), system active and reactive power control and transmission control for FACTs devices, tap changing transformers [120]. Further, the conventional schemes used in electric drive systems using power electronic devices are getting replaced by Fuzzy logic controllers for better performance [121]. Recently, power electronics technology is becoming an efficient method of interconnecting various distributed generation sources to utility networks [121].
The fuel cell is one of the prominent DG sources which require power electronic interface to change its generated power characteristics to that of the grid network. Conventionally, PI and PID controllers are used to generate pulses to control the operation of power electronic device used for interfacing of FC to grid [94], [122]. These conventional controllers may not give accurate performance when there is change in system parameters or when it is subjected to large variation in the load. The Fuzzy control is a practical alternative for a variety of challenging control applications, since it is a convenient method for constructing non-linear controllers by the use of heuristic information. Thus, there is a possibility to use fuzzy logic control for fuel cell [123], [124].

The basics of fuzzy set theory and fuzzy logic control are presented in this chapter. The detailed design of fuzzy logic controller for boost converter and for load side inverter is given in this chapter. This includes the design of membership functions and the rule base for the fuzzy controller. The Simulink implementation of the proposed FLC is also presented in this chapter. The developed FLC controller performance has been studied for isolated operation of fuel cell and the results are also reported in this chapter.

**4.2 FUZZY SET AND FUZZY CONTROL**

In 1965, Prof. L.A. Zadeh laid the foundations of fuzzy set theory [125] as a method to deal with the imprecision of practical systems. 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 [126]. This "imprecision" or fuzziness is the core of fuzzy sets or fuzzy logic applications. Fuzzy sets were proposed as a generalization of conventional set theory. Partially as result of this fact, fuzzy logic remained the purview of highly specialized and mathematical technical journals for many years. This changed abruptly with the highly visible success of several control applications in the late 1980s.
4.2.1 Fuzzy Sets and Terminology

Let $U$ be a collection of objects denoted generically by $(u)$, which could be discrete or continuous. $U$ is called the universe of discourse and $u$ represents the generic element of $U$.

**Definition 1:** Fuzzy set: A fuzzy set $F$ in a universe of discourse $U$ is characterized by a membership function $\mu_f$ which takes values in the interval $[0, 1]$ namely, $\mu_f : U \rightarrow [0,1]$. A fuzzy set may be viewed as a generalization of the concept of an ordinary set whose membership function only takes two values $\{0, 1\}$. Thus a fuzzy set $F$ in $U$ may be represented as a set of ordered pairs of a generic element $u$ in its universe of discourse $U$ and its grade of membership function: $F = \{(u, \mu_f(u))|u \in U\}$. When $U$ is continuous, a fuzzy set $F$ can be written concisely as $F = \{(u, \mu_f(u))|u \in U\}$ When $U$ is discrete, a fuzzy set $F$ is represented as

$$F = \sum_{i=1}^{n} \mu_f(u_i) / u_i$$  \hspace{1cm} (4.1)

**Definition 2:** Support, crossover Point, and Fuzzy Singleton: The support of a fuzzy set $F$ is the crisp set of all points $u$ in $U$ such that $\mu_f(u) > 0$. In particular, the element $u$ in $U$ at which $\mu_f(u) = 0.5$ is called the crossover point and a fuzzy set whose support is a single point in $U$ with $\mu_f(u) = 1.0$ is referred to as fuzzy singleton.

4.2.1.1 Fuzzy set theoretic operations

Let $A$ and $B$ be two fuzzy sets in $U$ with membership functions $\mu_A$ and $\mu_B$ respectively. The set theoretic operations of union, intersection and complement for fuzzy sets are defined via their membership functions.

**Definition 3:** Union: The membership function $\mu_{A \cup B}$ of the union $A \cup B$ is point wise defined for all $u \in U$ by

$$\mu_{A \cup B}(u) = \max(\mu_A(u), \mu_B(u))$$  \hspace{1cm} (4.2)
**Definition 4:** Intersection: The membership function $\mu_{A \cap B}$ of the intersection $A \cap B$ is point wise defined for all $u \in U$ by

$$
\mu_{A \cap B}(u) = \min(\mu_A(u), \mu_B(u))
$$

(4.3)

**Definition 5:** Complement: The membership function $\mu_{\bar{A}}$ of the complement of a fuzzy set $A$ is point wise defined for all $u \in U$ by

$$
\mu_{\bar{A}}(u) = 1 - \mu_A(u)
$$

(4.4)

**Definition 6:** Cartesian product: If $A_1, \ldots, A_n$, are fuzzy sets in $U_1, \ldots, U_n$ respectively, the Cartesian product of $A_1, \ldots, A_n$, is a fuzzy set in the product space $U_1 \times \ldots \times U_n$ with the membership function

$$
\mu_{A_1 \times \ldots \times A_n}(u_1, u_2, \ldots, u_n) = \min(\mu_{A_1}(u_1), \ldots, \mu_{A_n}(u_n))
$$

(4.5)

### 4.2.1.2 Linguistic variable and fuzzy set

**Definition 7:** Fuzzy Number: A fuzzy number $F$ in a continuous universe $U$, e.g., a real line, is a fuzzy set $F$ in $U$ which is normal and convex, i.e.,

$$
\max_u \mu_F(u) = 1, \quad \text{(normal)}
$$

(4.6)

$$
\mu_F(\lambda u_1 + (1-\lambda)u_2) \geq \min(\mu_F(u_1), \mu_F(u_2)), \quad \text{(convex)}
$$

(4.7)

$u_1, u_2 \in U, \lambda \in [0,1]$  

The use of fuzzy sets provides a basis for a systematic way for the manipulation of vague and imprecise concepts. In particular; we can employ fuzzy sets to represent linguistic variables. A linguistic variable can be regarded either as a variable whose value is a fuzzy number or as a variable whose values are defined in linguistic terms.

**Definition 8:** Linguistic Variables: A linguistic variable is characterized by a quintuple $(x, T(x), U, G, M)$ in which $x$ is the name of variable; $T(x)$ is the term set of $x$, that is, the set of names of linguistic values of $x$ with each value being a fuzzy...
number defined on U; G is a syntactic rule for generating the names of values of x; and M is a semantic rule for associating with each value its meaning. For example, if speed is interpreted as a linguistic variable, then its term set \( T \) (speed) could be

\[
T \text{(speed)} = \{ \text{slow, moderate, fast, very slow, more or less fast, . . . } \}
\]

Where, each term in \( T \) (speed) is characterized by a fuzzy set in a universe of discourse \( U = [0,100] \). It can be interpreted like “slow” as “a speed below about 40 mph,” “moderate” as “a speed close to 55 mph,” and “fast” as “a speed above about 70 mph.” These terms can be characterized as fuzzy sets whose membership functions are defined.

### 4.2.2 Fuzzy Logic Control

Fuzzy logic control (FLC) theory is a mathematical discipline based on vagueness and uncertainty. The fuzzy control does not need an accurate model of a plant. It allows one to use non-precise or ill-defined components. Fuzzy logic control is also non-linear and adaptive in nature that gives it a robust performance under parameter variation and load disturbances. This control technique relies on the human capability to understand the system’s behaviour and is based on qualitative control rules. Thus control design is simple since it is based only on IF….THEN linguistics rules [127]. Some of the advantages of the FLC may be enumerated as [128], [129]. A fuzzy controller can be designed to roughly emulate the human deductive process i.e., the process whereby one successively infers conclusions from their knowledge.

- Fuzzy controllers are more robust than PID controllers because they can cover wider range of operating conditions than PID, and can also operate with noise and disturbance of different natures.

- Developing the fuzzy controller is cheaper than developing a model based or other controllers for the same purpose.

- Fuzzy controllers are customizable, since it is easier to understand and modify their rules, which not only use human operator’s strategy but also is expressed in natural linguistic terms.
- It is easy to learn how fuzzy controllers operate and how to design and apply them to a real application.

- FLC provides systematic efficient framework for incorporating linguistic fuzzy information from human experts.

- Easy to understand and simplifies design complexity; thus simple, fast to implement and cost effective.

- Because of the rule based operation, any reasonable number of inputs can be processed and numerous outputs can be generated.

- Fuzzy control is a mode-free approach and provides non-linear controllers.

A fuzzy controller can be designed to roughly emulate the human deductive process i.e., the process whereby one successively infers conclusions from their knowledge. The functional architecture of the fuzzy system is composed of four basic elements; a fuzzy knowledge base (rule base and data base), an inference mechanism, a fuzzification interface and a defuzzification interface. The basic block diagram of fuzzy controller is given in Fig. 1, where a fuzzy controller is embedded in a closed-loop control system. The plant outputs are denoted by \( y(t) \), its inputs are denoted by \( u(t) \), and the reference input to the fuzzy controller is denoted by \( r(t) \).

![Fig. 4.1 Block diagram of fuzzy logic controller](image_url)
a) The fuzzification interface involves the following functions:

- measures the values of input variables,
- performs a scale mapping that transfers the range of values of input variables into corresponding universes of discourse,
- performs the function of fuzzification that converts input data into suitable linguistic values which may be viewed as labels of fuzzy sets.

The number of fuzzy sets defined in the input discourse and their specific membership functions define the fuzzification interface design. There are many types of different membership functions and their choice for a specific problem is not unique. The initial form of the membership functions can be obtained by using expert considerations or by clustering the input data.

b) The rule base comprises knowledge of the application domain and the attendant control goals. It consists of a “data base” and a “linguistic (fuzzy) control rule base:”

- The data base provides necessary definitions, which are used to define linguistic control rules and fuzzy data manipulation in an FLC.
- The rule base characterizes the control goals and control policy of the domain experts by means of a set of linguistic control rules.

In a FLC, the dynamic behavior of a fuzzy system is characterized by a set of linguistic description rules based on expert knowledge. For example, in the case of single input-single-output (SISO) fuzzy systems, fuzzy control rules have the form:

Rule: if x is A, then y is B

Where x and y are linguistic variables representing process state variables and one control variables. A and B are linguistic values of the linguistic variables x and y in the universe of discourse U. The relationship between the input signals and the fuzzy controller output is developed using fuzzy set theory and is described as a fuzzy relation matrix using assigned membership functions [130].
c) The decision making logic is the kernel of an FLC; it has the capability of simulating human decision making based on fuzzy concepts and of inferring fuzzy control actions employing fuzzy implication and the rules of inference in fuzzy logic.

d) The defuzzification interface performs the following functions:

- a scale mapping, which converts the range of values of output variables into corresponding universes of discourse,

- defuzzification, which yields a nonfuzzy control action from an inferred fuzzy control action.

There are several defuzzification methods including the centroid method [131] and the height method. The centroid method (also known as the center of gravity method) is the most common in use. This method selects the output value corresponding to the centroid (center of gravity) of the output membership function as the crisp value for an output. The defuzzification interface combines the conclusions reached by the fuzzy inference mechanism and provides a numeric value as an output. Overall, the fuzzy control design methodology, which primarily involves the specification of the rule base, provides a heuristic technique to construct non-linear controllers, and this seems to be one of its main advantages.

4.3. FUZZY LOGIC CONTROLLERS FOR SOFC

The output voltage of FC’s at the series of stacks is uncontrolled DC voltage, which fluctuates with load variations as well as with the changes in the fuel input. It has to be controlled by a DC/DC converter. The controlled voltage thus obtained is then fed to the DC/AC inverter. The power obtained from the inverter is supplied to the load directly (isolated mode) or to the grid. The voltage at the inverter output needs to be conditioned for interfacing the FC to the isolated load.
Fig 4.2 Simulink block diagram of SOFC with fuzzy logic controller for isolated operation

The Simulink block diagram of SOFC interfaced to isolated load using DC/DC Boost converter and PWM inverter topology with fuzzy logic controller is shown in Fig.4.2. The purpose of the DC/DC booster converter is to boost the fuel cell voltage, and to provide regulated DC voltage as an input to PWM inverter. The unregulated output voltage of the FC is fed to the dc/dc boost converter. Being unregulated it has to be adjusted to a constant average value (regulated dc voltage) by adjusting the duty ratio and voltage is boosted depending upon the duty ratio. The duty ratio of the boost converter is adjusted with the help of a fuzzy logic controller (FLC) as shown in Fig 4.2. The duty ratio is set at a particular value for the converter to provide desired average value of output voltage, and any fluctuation in the FC voltage due to change in fuel flow, change in the load or in the behaviour of FC due to the chemistry involved taking the output voltage away from the desired value. The FLC changes the duty ratio appropriately to get the desired average value. The boost converter responds quickly to the changes in the duty ratio. The duty ratio of the converter is changed by changing the pulses fed to the switch in the dc/dc converter circuit by the PWM generator.

The output of the dc/dc converter is a boosted voltage that is fed to the inverter stage. Two Fuzzy controllers are used to determine the switching pattern for the inverter.
using PWM technique to control the output voltage at the load terminals. One for direct voltage component \(V_{d\_control}\) and another for quadrature voltage component \(V_{q\_control}\).

### 4.3.1 Design of Fuzzy Logic Controller for Boost Converter

The general structure of a fuzzy controller is represented in Fig.4.1. There are many different ways to use fuzzy controllers in a closed loop control application. The steps involved in the design are:

- To select control elements and parameters as scaling factors for input and output signals.
- To partition the universe of discourse of the interval spanned by each variable into a number of fuzzy subsets, assigning each a linguistic label.
- To assign membership function for each fuzzy subset.
- To assign the fuzzy relational between the input and output fuzzy subsets, thus forming the rule base.
- To choose appropriate scaling factors for the input and output variables in order to normalize the variables to \([-1, 1]\) or \([0, 1]\) interval.
- To fuzzify the inputs or to classify the input data into suitable linguistic values or sets to the controller.
- To use fuzzy appropriate reasoning to infer the output contributed from each rule.
- To aggregate the fuzzy outputs recommended by each rule.
- To apply defuzzification technique to form a crisp output.
- To send the change of control action.

There are two major types of fuzzy control: the Mamdani type and the Sugeno type. They mainly differ in the fuzzy control rule consequent. The Mamdani fuzzy
controllers utilize fuzzy sets as the consequent whereas the Sugeno fuzzy controllers employ (linear) functions of input variables as the consequent. Both the types of fuzzy control have successfully been applied to solve practical control problems [126]. Presently almost all the fuzzy controllers are used and are treated as black-box controllers, which when constructed properly by the trial-and-error method could produce satisfactory results.

4.3.1.1 Fuzzy based Simulink model for boost converter

The fuzzy logic controller used in this work is of two input and single output Mamdani type. The input signal is the error ($\Delta V$) between the voltage across the capacitor ($V_{dc}$) and reference voltage. The FLC used for Boost converter is shown in Fig. 4.3. The two inputs to the fuzzy controller are error $e(k)$ and the change in error $\Delta e(k)$. The controlled output $u(k)$ is the duty ratio of the boost converter and the controller output is the change in the duty ratio $\Delta u(K)$. The change in duty ratio is fed to the PWM generator which changes the duty ratio accordingly and adjusts the output of the converter. The two inputs, error $e(k)$ and change in error $\Delta e(k)$ are multiplied by scaling factors $k_1$ and $k_2$ respectively and are then fed into fuzzy controller which is shown in Fig. 4.3.

![Fig. 4.3 Fuzzy controller for boost converter](image)

The error, change of error and the output of the controller are given as follows:
\[
e(k) = K_1(V_{\text{dc ref}} - V_{\text{dc}})
\]

(4.9)

\[
\Delta e(k) = K_2 \left( \frac{de(k)}{dt} \right)
\]

(4.10)

\[
u(k) = u(k-1) + K_3 \Delta u(k)
\]

(4.11)

Where \(V_{\text{dc ref}}\) is the reference DC Voltage, \(V_{\text{dc}}\) is the voltage across the capacitor, and \(\Delta u(k)\) is the change in duty ratio. The output of the fuzzy controller is the change in duty cycle \(\Delta u(k)\). It is scaled by linear gain \(K_3\). The scaling factors \(k_1, k_2\), and \(k_3\) have been tuned to obtain the required response. The value of scaling factor found to be \(k_1 = 2; k_2 = 102;\) and \(k_3 = 0.7\).

The three variables of FLC: the error, change in error and the change in control signal i.e. change in duty ratio have seven membership functions (MF) each. A triangle-shaped membership function has been used for fuzzy logic controller design. The fuzzy variables are expressed by linguistic variables such as PL for positive large, PM for positive medium, PS for positive small, Z for zero, NS for negative small, NM for negative medium, and NL for negative large. The linguistic dimensions for the MF’s are the same for the three variables. The basic fuzzy partition of membership functions for three variables is shown in Fig. 4.4. The membership functions for both inputs and outputs of the controller are defined on the common interval \([-1, 1]\).

![Fig. 4.4 Fuzzy membership function for \(e(k), \Delta e(k)\) and \(\Delta u(k)\)]

A rule in the rule base can be expressed in the form:
“If \( e(k) \) is NL and \( \Delta e(k) \) is NL, then the change in duty ratio, \( \Delta u(k) \) is NL”.

The rules set is based upon the knowledge and working of the system. The inference method used is basic and simple. Here the commonly used Min-Max method is implemented. The output membership function of each rule is given by the MIN operator, whereas the combined fuzzy output is given by the Max operator. The centroid defuzzification method has been considered that determines the crisp output value from the centre of gravity of the output membership function [131]. The membership functions of error “\( e(k) \)”, change in error “\( \Delta e(k) \)” and change in output “\( \Delta u(k) \)” are shown in Fig.4.4.

Basically, defuzzification is a mapping from a space of fuzzy control actions defined over an output universe of discourse into a space of nonfuzzy (crisp) control actions. It is employed because in many practical applications a crisp control action is required. A defuzzification strategy is aimed at producing a nonfuzzy control action that represents the best possible distribution of an inferred fuzzy control action. Unfortunately, there is no systematic procedure for choosing a defuzzification strategy [131]. At present, the commonly used strategies may be described as the max criterion, the mean of maximum, and the center of area (COA) or center of gravity. The widely used COA strategy generates the center of gravity of the possible distribution for a control action. In this work COA method has been used. This method obtains the center of area \( (x^*) \) occupied by the Fuzzy set. For a discrete membership function, it is given by:

\[
x^* = \frac{\sum_{i=1}^{n} x_{i} \mu (x_{i})}{\sum_{i=1}^{n} \mu (x_{i})}
\]  

(4.12)
Here, \( n \) represents the number of elements in the sample, \( x_i \)'s are the elements and \( \mu(x_i) \) is its membership function.

A FLC uses a rule base to perform its control action. The number of rules can be set as desired. For boost converter the rule base has been derived from the knowledge of DC–DC converters. The numbers of rules set for DC/DC boost converter control are 49, which are based upon the seven membership functions of the input variables. The rule base for FLC is shown in Table 4.1.

<table>
<thead>
<tr>
<th>Error (e)</th>
<th>NL</th>
<th>NM</th>
<th>NS</th>
<th>Z</th>
<th>PS</th>
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<tr>
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Table 4.1 Fuzzy rule base for duty ratio control of DC-DC boost converter

Fig. 4.5 illustrates the fuzzy rule viewer diagram for providing the change in duty ratio. The controller output is determined by rules as mentioned previously. Since the boost converter output is very sensitive to the duty ratio, to stabilize the system, the modified gains \( K_3 \) are applied in fuzzy control rules. The rule viewer diagram shows the rules that are active or how an individual membership function shapes influence the results. Figure 4.6 shows the surf view of fuzzy controller for providing change in duty ratio.
Fig. 4.5 Fuzzy rule viewer diagram for fuzzy controller's output, delta \[ u(k) \]

Only a portion of rule viewer is shown.

Fig. 4.6 Surf view of fuzzy controller providing change in duty ratio
4.3.2 Design of Fuzzy Logic Controller for PWM Inverter

The Simulink block diagram of FLC based voltage regulator for voltage source PWM inverter is shown in Fig.4.7. The two fuzzy controllers as shown in Fig 4.7 are employed one for direct voltage component \( v_d \) control and another for quadrature voltage component \( v_q \) control. The output of two fuzzy controllers are equivalent to reference voltage and are used for the determination of switching patterns using pulse width modulation technique which requires a balance set of three sinusoidal modulating signals along with triangular carrier signal of high frequency. The balanced set of three sinusoidal modulating signals is obtained by transforming \( v_d \) to \( v_q \) into \( v_{acv} \) quantities. In the fuzzy logic controller shown in Fig. 4.7, the voltage error and change in voltage error are the two inputs to the each Fuzzy logic controller. The output of each controller is equivalent to voltage reference. In general, the error \( e_d(k) \) is the difference between the direct component of reference voltage and voltage across the load whereas \( \Delta e_d(k) \) is the incremental variation and they are given as

\[
e_d(k) = K(v_{dref} - v_{d_{inv}})
\]  

(4.13)
\[ e_q(k) = K(v_{q\text{ref}} - v_{d_{\text{inv}}}) \]  
(4.14)

\[ \Delta ed(k) = K\left(\frac{de_d(k)}{dt}\right) \]  
(4.15)

\[ \Delta eq(k) = K\left(\frac{de_q(k)}{dt}\right) \]  
(4.16)

Where \(v_{d\text{ref}}\) is the reference for direct component of the voltage, \(v_{q\text{ref}}\) is the reference for quadrature component of the voltage \(V_{d_{\text{inv}}}\) is the direct component of the inverter voltage and \(V_{q_{\text{inv}}}\) is the quadrature component of the inverter voltage. The value of scaling factors associated with error, change in error and change in fuzzy controller output for both d-axis and q-axis are considered as \(k=2; 0.0005\) and 100 respectively.

A triangle-shaped uniformly distributed membership function has been used for fuzzy logic controller design. The basic fuzzy partition of membership functions for three variables are shown in Figure 4.8 (a) and (b). The value of each input and output variable is normalized in the range \([-1, 1]\), by using suitable scale factors. For each input variable in fuzzy controller ‘nine’ subset has been used. The fuzzy variables for input signals are expressed by linguistic variables as: NVL for negative very large; NL for negative large; NM for negative medium; NS for negative small; Z for zero; PS for positive small; PM for positive medium; PL for positive large and PVL for positive very large.

However for output variable, 17 subsets have been used which are completely defined such as NVVL for negative very-very large, NVL for negative very large, NL for negative large, NML for negative medium large, NM for negative medium, NMS for negative medium small, NS for negative small, NVS for negative very small, Z for zero, PVS for positive very small, PS for positive small, PMS for positive medium small, PM for positive medium, PML for positive medium large, PL for positive large, PVL for positive very large and PVVL for positive very-very large.
The fuzzy control rules are obtained from the behavior of the system and 81 rules are generated in total. If the error is NVL and change in error is also NVL, the control output is set as NVL to ensure that they are reduced significantly. Similarly if error is PVL and change in error is also PVL the control value is set to PVL so that they become zero. If both the error and change of error are Z, then the control is set to Z.

The complete control rules are given in Table 4.2. Center of gravity method used for defuzzification [131].
### Table: 4.2

<table>
<thead>
<tr>
<th>Rate of change of error (Δe)</th>
<th>NVL</th>
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<th>PM</th>
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<th>PVL</th>
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<td>PMS</td>
<td>PM</td>
<td>PML</td>
<td>PL</td>
<td>PVL</td>
</tr>
<tr>
<td>PVL</td>
<td>Z</td>
<td>PVS</td>
<td>PS</td>
<td>PMS</td>
<td>PM</td>
<td>PML</td>
<td>PL</td>
<td>PVL</td>
<td>PVVL</td>
</tr>
</tbody>
</table>

Table: 4.2 Linguistic control rule base for voltage regulation of PWM inverter

Fig. 4.9 Three dimensional form of fuzzy membership function for FLC of PWM inverter

### 4.4. SIMULATION RESULTS

The performance study on SOFC fuel cell with fuzzy logic controller in an isolated operation mode has been carried out using the model shown in Fig 4.2. The three phase resistive load has been considered for the case study. A series resistor -inductor (RL) filter is used at the load side of the inverter.
4.4.1 Performance of Fuzzy Controlled Boost Converter

Fig. 4.10 Fuel cell with step change in load (a) stack voltage (b) stack current

Fig. 4.10(a) and 4.10(b) show changes in fuel cell terminal voltage and current for varying loads. It is observed that for a change in load from 50 kW to 100 kW instantaneously, the fuel cell voltage and current takes about 50ms to reach a new steady state. At the start it is observed that fuel cell voltage and current both attain high values for very small time and then settle down to appropriate voltage and current.
Fig. 4.11 Boost converter (a) output voltage (b) current (c) power output for step load change

Fig. 4.11. (a) shows boost converter output voltage for step change in load. It is observed that the design of simple boost converter with fuzzy controller gives better
performance for changes in load without the use of any storage devices. The output voltage of boost converter is controlled with FLC. The above response indicates that fuzzy control is able to achieve faster transient response with better rejection to load variation and attains more stable state response. It is seen that large load variation has limited effects on the output voltage of fuzzy logic controlled boost converter. Hence, the design of simple boost converter gives better performance for an isolated application. Fig.4.11 (b) and Fig.4.11 (c) show the converter current and power response for step change in load. The above responses show the effect of power control for the change in load current from 64.4 A to 128.8 A. As the step change in load occurs at time $t = 0.05$ sec, a small transient is observed both in converter current and power response however they attain the appropriate value very fast. The output voltage of fuel cell changes with change in load. The FLC handles the changes well and controls the output of boost converter. Thus the Design of simple DC-DC boost converter using FLC gives better performance for varying load.

4.4.2 Performance of Fuzzy Controlled PWM Inverter

The comparison of simulated results between PI based and Fuzzy based controllers for step changing three phase resistive load is shown and discussed below. The PI based voltage control strategy of PWM inverter interfacing the SOFC to isolated load is discussed in chapter 3 of this Thesis. However its various simulated responses are compared with Fuzzy approach in this chapter. Resistive balanced load with a step change from 50kW to 100kW has been used to verify the effectiveness of proposed fuzzy controller over PI controller in voltage regulation of PWM inverter. Fig.4.12 (a) and Fig.4.12 (b) demonstrates the comparison of per-phase inverter output current between PI control and Fuzzy control with variation in the load. The PI control response contains large amount of harmonics compared to fuzzy control response. So fuzzy controller offers good performance even with change in load as compared to PI controller.
Fig. 4.12 Inverter per phase output current with step change in load with (a) PI controller (b) FLC controller

Fig. 4.13 illustrates the comparison of simulated results between PI control and Fuzzy control for three phase balanced resistive load. Fig. 4.13(a) shows the voltage across the load with PI controller for a step change in load while Fig. 4.13 (b) portrays the voltage across the load with fuzzy controller under the same conditions. It is seen that
purposed fuzzy controller can effectively track the reference voltage and is insensitive to the load conditions like PI controller. With fuzzy controller, the voltage contains fewer harmonic compared to PI controller.

Fig. 4.13 Load terminal voltage for a step change in the load with (a) PI controller (b) FLC
4.14 Load current with step change in the load with (a) PI controller (b) FLC

The responses of three phase load currents with step change in load are shown in Fig.4.14 (a) and in Fig.4.14 (b) for both PI control and Fuzzy controller. From the simulation results it is observed that at time $t=0.5$ sec. when the load is changing from 50kW to 100kW, the load current has high transient response with PI controller than Fuzzy controller. Also the current response with PI controller takes more time to attain steady value than fuzzy controller.

The dynamic response of load voltages with step change in load under d-q reference with PI and fuzzy controller are presented in Fig.4.15 (a) and Fig.4.15 (b). The load voltage under d-q reference with PI controller contains more variation compared to fuzzy controller.
Fig. 4.15 Dynamic response of load voltage under dq reference frame with (a) PI controller (b) FLC

Fig. 4.16 Power response curve of $P_{fc}$ and $P_{Load}$ under step load change with (a) PI (b) FLC
The power supplied by the fuel cell to the load with PI controller has more transients compared to Fuzzy controller. Also the PI controller requires more time to attain a stable value than Fuzzy controller.

4.5. CONCLUSION

Fuzzy logic control is a practical alternative for a variety of challenging control applications. A fuzzy logic control strategy has been developed and employed in place of conventional PI controllers for connecting SOFC based DG system to isolated load. A FLC has been designed for boost converter that adjust duty ratio of boost converter to get regulated dc voltage output of required value. Two fuzzy logic controllers have been used for voltage source PWM inverter, one for direct voltage component control and the other for quadrature voltage component control. The various performances of SOFC based DG in isolated mode with FLC and PI controller have been analyzed and compared. The fuzzy control method is less sensitive to step load change compared to PI control method. Thus dynamic performance of SOFC system with fuzzy logic controller is found to be more improved as compared to PI controller.