CHAPTER 5

MODIFIED FUZZY BASED MAXIMUM POWER POINT TRACKING ALGORITHM

5.1 INTRODUCTION

The prime reasons for the low electrical efficiency of photovoltaic system are variation in solar insolation level, aging and load current. To overcome this problem, Masoum et al (2002) proposed a method to track the MPP with the help of a fuzzy controller and it determined the suitable firing angle for the converter which was used to supply voltage to suitable loads. The varying signals are cell temperature, irradiation and the wind velocity. The predicted signal is maximum power from the PV module. The data collected on basis of different seasons namely, spring, autumn and a rainy season. The fuzzy controller is studied and analyzed depending on the type of the season.

Mahmoud et al (2000) presented a simulation study of a fuzzy logic controller (FLC) for a Cuk converter in a stand alone photovoltaic (PV) energy scheme. The dc-dc power converters are used to convert the unregulated dc input into a regulated dc output at a desired voltage level. Wilamowski et al (2002), proposed a method, which sensed open circuit voltage and short circuit current used for optimum control with a fuzzy controller. The short circuit current of PV cell represents illumination, and the open circuit voltage carry on information about the temperature.
To overcome the problems of non-linearity in neural network, Simoes and Franceschetti (1999) proposed to track the maximum power point with the help of a fuzzy network system. The input parameters used were change in cell temperature, irradiation and the wind velocity. These parameters were fed into the fuzzy controller which was trained using centroid method, and it determined the suitable firing angle for the inverter used to supply voltage to suitable loads.

This technique uses many look up tables given by Anil Misra and Hukmani (2002). The tracker had fine dynamic behavior with limited accuracy. The main function of the MPPT is to adjust its input voltage, which is also the PV panel voltage in such a way that it corresponds to the voltage where the panel delivers maximum power.

5.2 FUZZY SYSTEM

Fuzzy Logic is much closer in spirit to human thinking and natural language than the traditional logical system which was discussed in Klir and Bo Yuan (2000). Basically, it provides an effective means of capturing the approximate, inexact nature of the real world. Figure 5.1 shows the configuration of fuzzy logic controller (FLC). The essential part of the fuzzy logic controller is a set of linguistic control strategy based on expert knowledge into an automatic control strategy.
Ueno (1991) proposed the advantages of the usage of fuzzy controller over the conventional method which was considered to be comparatively better. The FLC is considered as a good methodology because it yields results superior to those obtained by conventional control algorithms. In particular the FLC is useful in the following two cases:

1. The control processes are too complex to analyze by conventional quantitative techniques.

2. The available sources of information are interpreted qualitatively, inexactlty, or uncertainly.
The advantages of FLC are summarized as follows:

**Parallel or Distributed Control:** In the conventional control system, a control action is determined by single control strategy such as \( \mu = f(x_1, x_2, \ldots, x_n) \). But in FLC, the control strategy is represented by multiple fuzzy rules, and thus it is easy to represent complex systems and nonlinear systems.

**Linguistic control:** The control strategy is modeled by linguistic terms and thus it is easy to represent the human knowledge.

**Robust control:** There are more than one control rule and thus, in general, one error is not fatal for the whole system.

A self integrating knowledge based power quality events classifier is developed using the automatic generation of rules and membership functions using expert systems given by Ross (1997). This method is categorized into the following four types:

1. Learning fuzzy membership functions with fixed fuzzy rules.
2. Learning fuzzy rules with fixed membership functions.
3. Learning fuzzy rules and membership functions in stages namely involving good fuzzy rule sets using fixed membership functions, tuning membership functions using the derived fuzzy rule sets.
4. Learning fuzzy rules and membership functions simultaneously.
Fuzzy logic and fuzzy sets are tools for expressing and operating on knowledge which is in precise, or where the interpretation is highly subjective and depends strongly on context. The elements of the fuzzy model are:

1. Knowledge based of fuzzy rules
2. Fuzzy model: fuzzy sets that model the system variables
3. Fuzzifier: converts system inputs into a fuzzy format
4. Fuzzy inference system: executes all the fired rules and generates a new fuzzy output set
5. Defuzzifier: produces a crisp output from the fuzzy set
6. A fuzzy set is a set whose elements have a degree of membership attached to each one.

5.3 CONFIGURATION OF FUZZY LOGIC CONTROLLER

There is no systematic procedure for the design of an FLC. The configuration consists of four main components: fuzzification interface, knowledge base, decision-making logic, and defuzzification interface.

1. The Fuzzification interface transforms input crisp values into fuzzy values and it involves the following functions.
   - Receives the input values.
   - Transforms the range of values of input variable into corresponding universe of discourse.
   - Converts input data into suitable linguistic values (fuzzy sets).

   This component is necessary when input data are fuzzy sets in the fuzzy interface.
2. The knowledge base contains knowledge of the application domain and the control goals. It consists of a data base and a linguistic rule base.

- The data base contains necessary definitions which are used in control rules and data manipulation.
- The linguistic rule base defines the control strategy and goals by means of linguistic control rules.

3. The decision making logic performs the following functions:

- Simulates the human decision making procedure based on fuzzy concepts.
- Infers fuzzy control actions employing fuzzy implication and linguistic rules.

4. The defuzzification interface the function performs

- A scale mapping which converts the range of output values into corresponding universe of discourse.
- Defuzzification which yields a nonfuzzy control action from an inferred fuzzy control action.

5.3.1 Choice of State Variables and Control Variables

Before starting the detailed procedure of the FLC design, the variables have to be chosen as discussed by Konstantaras (2000). A fuzzy control system is designed to control a process, and thus it is needed to determine state variables and control variables of the process. The state variables become input variables of the fuzzy control system, and the control variables become the output variables. Selection of the variables depends on
expert knowledge on the process. In particular, variables such as state, state error deviation, and the state error integral are often used.

5.3.2 Fuzzification Interface Component

In the Fuzzification component, there are three main issues to be considered:

1. **Scale mapping of input data**: First decide a strategy to convert the range of values of input variables into corresponding universe of discourse. When an input value comes through a measuring system, the values were located in the range of input variables. For example, if the range of input variables was normalized between -1 to 1, a procedure is needed which maps the observed input value into the normalized range.

2. **Strategy for noise**: When observed data are measured, the data is disturbed by random noise. In this case, a Fuzzification operator should convert the probabilistic data into fuzzy numbers. Computational efficiency is enhanced since fuzzy numbers are much easier to manipulate than random variables. The observed data does not contain vagueness, and considered as the observed data of a fuzzy singleton. A fuzzy singleton is a precise value and no fuzziness is introduced by Fuzzification in this case. In control application, the observed data are usually crisp and used as fuzzy singleton inputs in the fuzzy reasoning.
3. **Selection of Fuzzification function:** A Fuzzification operator has the effect of transforming crisp data into fuzzy sets.

5.3.3 **Knowledge Base Component**

**Data Base:** The knowledge base of an FLC is comprised of two parts: a data base and a fuzzy control rule base. In the data base part, there are four principal design parameters for an FLC: discretization and normalization of universe of discourse, fuzzy partition of input and output spaces, and membership function of primary fuzzy sets.

1. **Discretization and Normalization of universe of discourse:**
   The modeling of uncertain information with fuzzy sets raises the problem of quantifying such information for digital computers. A universe of discourse in an FLC is either discrete or continuous. If the universe is continuous, a discrete universe is formed by a discretization procedure. A data set is also normalized into a certain range of data.

2. **Discretization of universe of discourse:** It is often referred to as quantization. The quantization discretizes a universe into a certain number of segments. Each segment is labeled as a generic element and forms the discrete universe. A fuzzy set is then defined on the discrete universe of discourse. The number of quantization levels affects an important influence on the control performance, and thus it is large enough to give adequate approximation. That number is determined by considering both the control quality and the memory storage in computer.
3. **Normalization of a universe of discourse:** It is a discretization into a normalized universe. The normalized universe consists of finite number of segments. The scale mapping is uniform, non uniform or both.

4. **Fuzzy Partition of input and output spaces:** A linguistic variable in the antecedent of the rule forms a fuzzy input space, while that in the consequent of the rule forms a fuzzy output space. In general, a linguistic variable is associated with a term set. A fuzzy partition of the space determines how many terms exist in a term set. This is the same problem to find the number of primary fuzzy sets (linguistic terms).

There are five linguistic terms often used in fuzzy interface:

- NB: Negative big
- NS: Negative small
- ZE: Zero
- PS: Positive small
- PB: Positive big

5.3.4 **Membership Function of Primary Fuzzy Sets**

There are various types of membership functions such as triangular, trapezoid, and bell shapes are used.

**Rule Base:** A fuzzy system is characterized by a set of linguistic statements usually represented by in the form of “if then” rules.
**Source of fuzzy control rules:** There are two principal approaches to the derivation of fuzzy control rules. The first is a heuristic method in which rules are formed by analyzing the behavior of a controlled process. The derivation relies on the qualitative knowledge of process behavior. The second approach is basically a deterministic method which is systematically determined the linguistic structure of rules:

- Expert experience and control engineering knowledge: operating manual and questionnaire.
- Based on operators control actions: observation of human controllers actions in terms of input output operating data.
- Based on the fuzzy model of a process: linguistic description of the dynamic characteristics of a process.
- Based on learning: ability to modify control rules such as self-organizing controller.

To determine the operating point corresponding to maximum power for different insolation levels, the maximum power point was determined using the conventional derivative methods. A new fuzzy based logic controller is proposed to determine the maximum power as discussed by Won et al (1994). A dc/dc converter is utilized between the panel and the load for the purpose of MPP tracking. The maximum power point is tracked with the help of a fuzzy controller and it determines the suitable firing angle for the converter which is used to supply voltage to suitable loads as discussed by Senjyu and Uezato (1994).
5.4 PHOTOVOLTAIC SYSTEM USING FUZZY LOGIC

Solar cells have non-linear insolation, temperature and degradation dependent V-I and P-I characteristics as discussed by Khaehintung et al (2004). The operating point corresponding to the maximum output power changes with change in environmental and load conditions were suggested by Simoes et al (1999). The non-linear characteristics of M parallel strings with N series cells per string is given in equation (5.1)

\[
V_{SA} = \frac{N}{\lambda} \ln(I_{SC} - I_{SA} + M I_0) - \frac{N}{M} R_S I_{SA}
\]

(5.1)

where

- \( I_{SC} \) is the cell short circuit current (ampere),
- \( I_{SA}, V_{SA} \) are the output current and voltage of solar array,
- \( I_0 \) is the reverse saturation current,
- \( R_S \) is the series cell resistance and
- \( \lambda \) is the constant coefficient and depends on the cell material.

The equivalent circuit of the proposed PV array is given in Figure 5.2.

![Figure 5.2 Equivalent Circuit of the Proposed PV Array](image-url)
5.5 PROPOSED MODEL USING FUZZY SYSTEM

Figure 5.3 shows the proposed model of the PV system. In this model, the PV array is connected to the fuzzy logic controller block which is simulated by writing the fuzzy rules. The output of fuzzy controller is given to the power conditioning unit to trigger the inverter, which in turn supplies to the load.

![Block Diagram of the Proposed Model](image)

Figure 5.3 Block Diagram of the Proposed Model

Figure 5.4 shows the fuzzy controller block which consists of fuzzifier, decision making and de-fuzzifier units. The output of fuzzy controller is a fuzzy subset. The input signals are Error E and Change in Error \( \Delta E \). Once E and \( \Delta E \) are calculated and converted into linguistic variables, the fuzzy logic controller output, typically the change in Duty Cycle \( \Delta D \) is found.

Nopporn Patcharaprakiti et al (2005) proposed the triangular shape of the membership function that presumed for any particular input there is only one dominant fuzzy subset.
5.6 FUZZIFICATION

Fuzzy controller inputs are measured from the panel output. Figure 5.5 shows the triangular membership function of input and output variables in which membership functions of input variables E and ΔE is given in equation (5.2).

Five fuzzy subsets are considered for membership functions of the output variable. These input variables are expressed in terms of linguistic variables such as Z (zero), NS(Negative small), NB(Negative big), PS(positive small) and PB(positive big) being basic fuzzy subsets.

\[ \Delta E (n) = E (n) - E(n-1) \]
\[ E (n) = \frac{[ P (n) – P(n-1)]}{[V (n) – V(n-1)]} \]  

where E is error and ΔE is change in error
Figure 5.5 Fuzzy Membership Functions for (a) Input Variable Error \( E \) (b) Input Variable Change in Error \( \Delta E \) (c) Output Variable Change in Duty Cycle \( \Delta D \)
5.7 **DEFUZZIFICATION**

The output of fuzzy controller is a fuzzy subset. As the actual system requires a non-fuzzy value of control, defuzzification is required which is shown in block diagram Figure 5.4. The center of area (COA) algorithm is used for defuzzification of output control parameter. The flowchart of this algorithm is shown in Figure 5.6 from which the value of change in duty cycle \( \Delta D \) is found from the equation (5.3).

\[
\Delta D = \sum \mu(D_i) D_i \sum \mu(D_i)
\]  

(5.3)

where \( D_i \) are the centers of Max-Min composition output membership functions and \( \Delta D(k) \) \( \Box \) is the output of fuzzy processor.

Figure 5.6  Flow Chart for Fuzzy Logic Controller
5.8 FUZZY RULE BASE

Table 5.1 shows the fuzzy rule base. From this the following fuzzy rules were formulated.

Table 5.1 Fuzzy Rule Base

<table>
<thead>
<tr>
<th></th>
<th>NB</th>
<th>NS</th>
<th>ZE</th>
<th>PS</th>
<th>PB</th>
</tr>
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<tbody>
<tr>
<td>NB</td>
<td>ZE</td>
<td>ZE</td>
<td>NB</td>
<td>NB</td>
<td>NB</td>
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<tr>
<td>NS</td>
<td>ZE</td>
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<td>PS</td>
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<td>PS</td>
<td>ZE</td>
<td>ZE</td>
</tr>
<tr>
<td>PB</td>
<td>PB</td>
<td>PB</td>
<td>PB</td>
<td>ZE</td>
<td>ZE</td>
</tr>
</tbody>
</table>

1. If (E is NB) and (delE is NB) then (delD is Z) (1)
2. If (E is NB) and (delE is NS) then (delD is Z) (1)
3. If (E is NB) and (delE is Z) then (delD is NB) (1)
4. If (E is NB) and (delE is PS) then (delD is NB) (1)
5. If (E is NB) and (delE is PB) then (delD is NB) (1)
6. If (E is NS) and (delE is NB) then (delD is Z) (1)
7. If (E is NS) and (delE is NS) then (delD is Z) (1)
8. If (E is NS) and (delE is Z) then (delD is NS) (1)
9. If (E is NS) and (delE is PS) then (delD is NS) (1)
10. If (E is NS) and (delE is PB) then (delD is NS) (1)
11. If (E is Z) and (delE is NB) then (delD is NS) (1)
12. If (E is Z) and (delE is NS) then (delD is Z) (1)
13. If (E is Z) and (delE is Z) then (delD is Z) (1)
14. If (E is Z) and (delE is PS) then (delD is Z) (1)
15. If (E is Z) and (delE is PB) then (delD is PS) (1)
16. If (E is PS) and (delE is NB) then (delD is PS) (1)
17. If (E is PS) and (delE is NS) then (delD is PS) (1)
18. If (E is PS) and (delE is Z) then (delD is PS) (1)
19. If (E is PS) and (delE is PS) then (delD is Z) (1)
20. If (E is PS) and (delE is PB) then (delD is Z) (1)
21. If (E is PB) and (delE is NB) then (delD is PB) (1)
22. If (E is PB) and (delE is NS) then (delD is PB) (1)
23. If (E is PB) and (delE is Z) then (delD is PB) (1)
24. If (E is PB) and (delE is PS) then (delD is Z) (1)
25. If (E is PB) and (delE is PB) then (delD is Z) (1)

5.9 Fuzzy Results

Figure 5.7 (a), (b) and (c) shows the membership functions of error (E), change in error (ΔE) and change in duty cycle (ΔD). The corresponding output is viewed in rule viewer as shown in Figure 5.8.
Figure 5.7  Simulation results of fuzzy membership function (a) Error  
(b) Change in Error (c) Change in duty cycle
Figure 5.8 Fuzzy Output in Rule Viewer
Figure 5.9 shows the surface viewer of $\Delta D$ with respect to $\Delta E$ and $E$. This figure indicates the relationship among the elements. It is found that according to the variations the corresponding duty ratio is predicted. The results are tabulated in Table 5.2. For different values of $E$ and $\Delta E$ the corresponding output $\Delta D$ is found.
Table 5.2 Fuzzy Outputs

<table>
<thead>
<tr>
<th>∆E Change in error</th>
<th>0</th>
<th>0</th>
<th>0</th>
<th>0</th>
<th>0</th>
<th>-50.8</th>
<th>-78</th>
<th>77.2</th>
</tr>
</thead>
<tbody>
<tr>
<td>E error</td>
<td>0</td>
<td>-0.0234</td>
<td>-0.039</td>
<td>0.0202</td>
<td>0.0386</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>∆D Change in duty cycle</td>
<td>0</td>
<td>-0.0203</td>
<td>-0.0375</td>
<td>0.02</td>
<td>0.0308</td>
<td>-0.00601</td>
<td>-0.0186</td>
<td>0.0181</td>
</tr>
</tbody>
</table>

5.10 SIMULATION MODEL

For the simulation of fuzzy MPPT with solar panel and resistive load the Matlab/ Simulink software and its features are used. Figure 5.10 shows the Matlab model of the PV system. The input parameters are obtained from the solar panel (PV Array) and then fed to the fuzzy controller as suggested by Tang-Kai et al (2004).

Figure 5.10 Simulation Model of PV System Using Fuzzy Controller
5.10.1 PV Array

The Photovoltaic module (PV) is used to track down the sunlight into useful form of electrical energy. This PV array is used to determine the cell temperature and the value of irradiation. For simulation purposes, the readings of cell temperature and irradiation have been tabulated down periodically for every one hour. Using these values, a proto-type mathematical model is developed, which shows the output response based on dynamic variation in input parameters.

5.10.2 Fuzzy Controller Block

This simulates the fuzzy MPPT process and computes the desired duty cycle of the buck converter using the test data and the fuzzy controller unit. This block performs the fuzzification, fuzzy rule algorithm and defuzzification processes. Fuzzification is done using triangular membership functions and each physical variable is divided into a number of crisp inputs. The output is given to the PWM block.

5.10.3 PWM Block

It generates the pulse signals for the buck converter based on the desired duty cycle. The desired duty cycle is obtained from the fuzzy controller. The variation in the duty cycle is being monitored continuously and a feedback loop is provided to efficiently generate those switching signals.
5.10.4 Inverter Block

The inverter is used to provide supply to an ac load. In case of consumer requiring dc supply, the inverter block is removed and the boost converter alone is present which will directly feed the dc load.

5.11 SIMULATION RESULTS

For the simulation of fuzzy MPPT with solar panel and resistive load the Matlab/ Simulink software and its facilities are used. Figure 5.11 shows the simulation results of the PWM pulses output, inverter output voltage and current waveform. It is noted that the system is not susceptible to sudden variations in the input parameters.

Figure 5.11 Simulation Result of Fuzzy Controller
5.12 CONCLUSION

The simulation result shows that the system is not susceptible to sudden variations in the input parameters and in stable conditions. The output obtained confirms the presence of a maximum power point which is given to the fuzzy controller to enhance the maximum power. If the error increases, the duty cycle variation also increases. Climatic conditions play a vital role. If the input parameters to be controlled increases, fuzzy logic controller is not useful, and effective rules cannot be determined. In order to overcome this limitation the neuro-fuzzy system is introduced.