Control of Delta power for multistring PV inverters by Anfis MPPT and CPG mode

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Abstract **-With a still increasing penetration level of grid connected photovoltaic (PV) systems, more advanced active power control functionalities have been introduced in certain grid regulations. A delta power constraint, where a portion of the active power from the PV panels is reserved to support frequency deviation. In this paper , Multistring PV inverter configuration is adopted to realize delta power control (DPC) for grid-connected PV systems. This control strategy is a combination of maximum power point tracking (MPPT) and constant power generation (CPG) modes. This paper proposes adaptive neuro-fuzzy inference system (ANFIS) for maximum power point tracking of photovoltaic systems. In this control scheme, one PV string operating in the MPPT mode estimates the available power, whereas the other PV strings regulates the total PV power by the CPG control strategy in such a way that the delta power control for the entire PV system is achieved.**

The implementation of ANFIS under the matlab/Simulink environment shows that this technique is more efficient and robust than FLC .The results have confirmed the effectiveness of the proposed DPC strategy, where the power reserve according to the delta power control is achieved under several operating conditions.

Index Terms—Delta power control, maximum power point tracking (MPPT), fuzzy logic control ,photovoltaic (PV) system, constant power generation (CPG) control, grid-connected power converters.

I. INTRODUCTION

Renewable energy sources play an important role in electrical energy generation. The increasing renewable energy penetration together with the price reduction of photovoltaic modules supported the development of large scale photovoltaic power plants connected to the medium and low voltage grid. Many concerns are emerging about the electrical system stability when it is connected to renewable sources. Once, photovoltaic plants where thought to reach always the maximum power point and to extract the maximum power available [1]. Nowadays, there are new challenges that photovoltaic plants have to overcome for ensuring the production and control with a variable energy resource as solar radiation. Photovoltaic generation components and control are being investigated according to new grid requirements proposed by Puerto Rico and South Africa [2]. The control of active power should match the variability of solar energy during the day and it is divided into absolute production, delta production and power gradient . In the requirements of PREPA it is established that in normal operating conditions the system should be able to provide a reduction of active power in the connection point with steps of 10% of the estimated power [2]. Besides, in grid codes of NERSA, the active power capability value shall not be less than 3% of the available power in order to guarantee a reserve for frequency stabilization [3] .

First of all the literal review starts with a focus into the PV generator topologies. Then, there is a description of the principal topologies of PV plants currently diffused. Each technique has its own advantages and basically there are three main topologies: central, string and multi-string. This section analyzes the main characteristics of different topologies with a particular focus on their principal advantages and disadvantages.

Central topology:

This topology interconnects several thousands of PV panels to one inverter. Each array has several strings connected in parallel, the strings are composed by PV panels connected in series and strings are connected with inverters. Generally, it is used for large PV systems with high power output [2]. The main characteristics of this topology are low MPPT efficiency and flexibility but high robustness.

String topology:

This technique connects one inverter per string. It generates more power than the central topology in non-uniform conditions but costs of installation are high due to greater number of inverters [2].

Multi-string topology:

The multi-string topology connects one PV string to a dc-dc converter for tracking the maximum power point and then several converters are connected to one inverter via a dc bus. This technique is featured by higher efficiency because there is one dedicated MPPT per string [2].

When looking into the prior artwork, there are mainly three approaches [1] to realize delta power control (DPC). Firstly, integrating energy storage system where surplus PV power can be stored but it is not feasible as it cost high and limited life time. Second solution is by dumping a load to dissipate surplus PV power which increases overall complexity of the system. The third approach is by modifying the MPPT algorithm offers a more cost-effective solution.

The objective of the author is to propose an intelligent technique for MPP to improve performance of PV system. Artificial intelligence (AI)-based methods are increasingly used in renewable energy systems due to the flexible nature of the control offered by such techniques. The AI techniques are highly successful in nonlinear systems due to the fact that once properly trained they can interpolate and extrapolate the random data with high accuracy.

Fuzzy logic has the capability of transforming heuristic and linguistic terms into numerical values through fuzzy rules and membership functions . It also provides the heuristic output by quantifying the actual numerical data into heuristic and linguistic terms. However, the shortcoming of fuzzy computation is obtaining correct fuzzy rules and membership functions which heavily rely on the prior knowledge of the system. The ANFIS integrates the neural network and fuzzy logic, thus this synergy offers the most powerful artificial intelligence technique . This paper thus uses ANFIS techniques to determine the maximum power capability of a PV module for variable solar irradiance and temperature conditions. The other maximum power point tracking (MPPT) algorithms such as perturb and observe, incremental conductance and their improvements suffer from drawbacks such as oscillations at the operating point and lack in fast dynamic response. The speed of the algorithm in locating the correct operating point of PV is a crucial factor especially when operating in grid interactive mode. The proposed technique of using ANFIS-based MPPT offers highly precise and fast control with robust operation and is highly suitable for application in PV generation systems [4].

The rest of this paper is arranged as follows: Section 2 explains control scheme for DPC strategy. Section 3 describes the ANFIS based MPPT control. Section 4 describes grid connected PV system. Simulation results obtained by matlab environment are presented in Section 5.

II. CONTROL SCHEME OF DPC STRATEGY FOR MULTISTRING PV INVERTERS

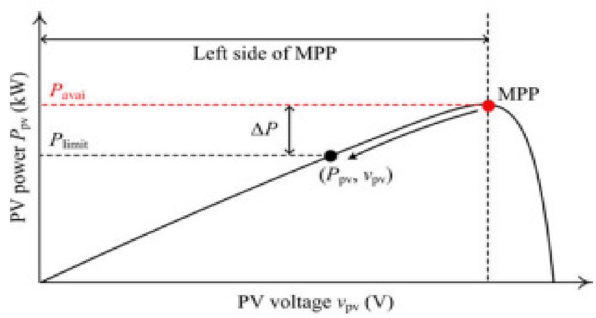

Fig.1 PV characteristics of pv panel

In this approach, the operating point of the PV system in the power–voltage (P–V) curve is regulated below the maximum power point (MPP) in order to limit the PV power P_{pv} [5] to a certain level P_{limit}. The paper is focussed on active power control of PV string, where the MPPT and the CPG operation are co-ordinately controlled. The PV system needs to reserve a certain amount of PV power ΔP during operation for possible frequency regulation, where the delta power constraint can be summarized as

$$Ppv = Pavai - \Delta P$$

In order to control the PV output power Ppv according to the DPC strategy in (5), the other two quantities (i.e., the available power Pavai and the amount of power reserve ΔP) must be known. Typically, the amount of power reserve ΔP can either be calculated as a function of the grid frequency deviation or set by the system operator. the reference power reserve ΔP is chosen to be 70 W.

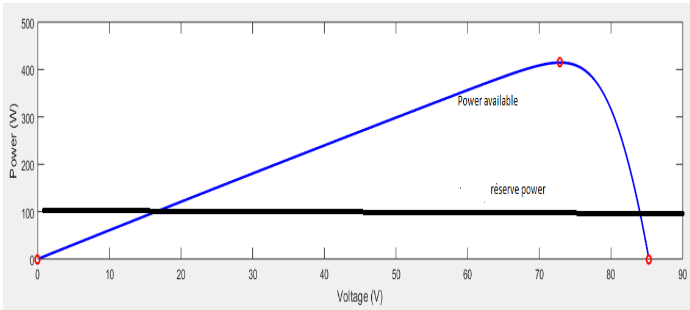

Fig. 2 PV output power with reserve power of 100W

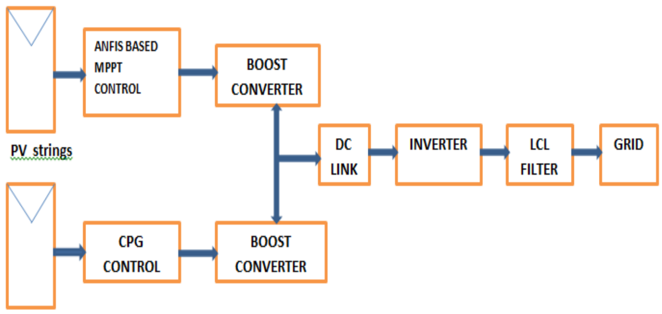

Fig.3 Block diagram for control scheme of DPC Strategy

The MPPT is achieved using ANFIS. It is known from literature that the PV system needs to be operated at a specified voltage for extracting maximum available power. The ANFIS is trained for acheiving maximum power delivery from the PV panels. The inputs to the ANFIS are voltage and current.

Estimation of available output power in MPPT mode

When solar irradiance is not measured, it is a challenging task to estimate available PV power. In commercial scale PV systems, PV systems are located close to each other. Most PV strings have same solar irradiance and temperature profiles, and therefore same power production profiles. If master PV string operate in MPPT mode, its P_{pv1} can be used to estimate available power of the rest PV strings [5]. Total available power of the PV plant Pavai can be simply estimated by

$$P_{avai} = N_{pv}\ P_{pv1}$$

Where N_{pv} is the ratio between the rated power of the total PV plant and master PV string. If the PV system consists of two PV string with the equal rated power , then power ratio can be determined as Npv = 2. The rated power of master PV string is half of total PV system rated power.

III. ANFIS BASED MPPT

The Adaptive Neuro-Fuzzy Inference System technique was originally presented by Jang in 1993 [6]. ANFIS is a simple data learning technique that uses Fuzzy Logic to transform given inputs into a desired output through highly interconnected Neural Network processing elements and information connections, which are weighted to map the numerical inputs into an output.

ANFIS combines the benefits of the two machine learning techniques (Fuzzy Logic and Neural Network) into a single technique [6]. An ANFIS works by applying Neural fuzzy systems which can acquire knowledge automatically by learning algorithms of neural networks. ANFIS constructs an input output mapping based both on human knowledge (in the form of fuzzy if then rules) and on generated input Network learning methods to tune the parameters of a Fuzzy Inference System (FIS). There are several features that enable ANFIS to achieve great success

In neuro-fuzzy systems, neural networks are incorporated into output data pairs by using a hybrid algorithm that is the combination of the least-squares and backpropagation gradient descent method. In this paper ANFIS reference model is developed using ANFIS editor of Matlab/Simulink software package.

Different rules cannot share the same output membership function. The number of membership functions must be equal to the number of rules. To present the ANFIS architecture, two fuzzy IF-THEN rules based on a first order Sugeno model are considered [7]:

$Rule_1$ = IF x is A_1 AND y is B_1 THEN

$$f_1 = p_1 x + q_1 y + r_1$$

$Rule_2$ = IF x is A_2 AND y is B_2 THEN

$$f_2 = p_2 x + q_2 y + r_2$$

- It refines fuzzy IF-THEN rules to describe the behavior of a complex system; .
- It does not require prior human expertise; .
- It is easy to implement; .
- It enables fast and accurate learning; .
- It offers desired data set; greater choice of membership functions to use; strong generalization abilities; excellent explanation facilities through fuzzy rules; and .
- It is easy to incorporate both linguistic and numeric knowledge for problem solving

ANFIS Architecture

For simplicity assume the fuzzy inference system under consideration has two inputs x and y and one output z [8].

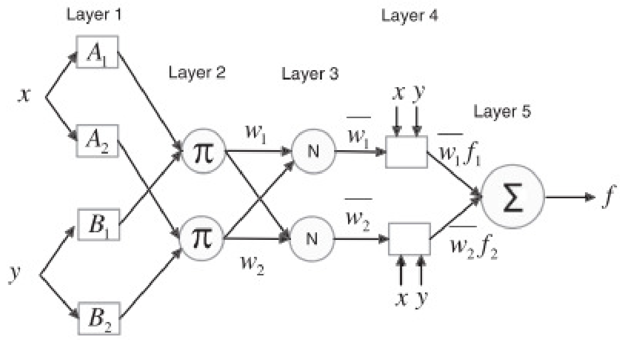

Fig 4 Anfis architecture

Algorithm For Neuro-Fuzzy Based MPPT

STEP 1: Fuzzification Step (Input Step):

The First Layer

This layer is a basic fuzzification layer where the crisp inputs are allocated to relative fuzzy values .The generalized bell shaped member ship functions are utilized. The output of the layer one for i^{th} membership function is calculated as:

$$O_i^1 = \mu_{A_i}(G) = e^{\left\{-\left(\frac{x-c_i}{a_i}\right)^2\right\}^{b_i}}$$

$$O_i^1 = \mu_{B_i}(T) = e^{\left\{-\left(\frac{y-c_i}{a_i}\right)^2\right\}^{b_i}}$$

Where O_i^1 is the output of first layer, G is the Insolation and T is the temperature (crisp input values) for this application. A_i and B_i are linguistic labels characterized by appropriate membership functions, a_i b_i , c_i are the premise parameters described from the characteristics of bell shaped function. These premise parameters are fixed in the forward pass and are updated in the adaptation process by gradient descent method in the backward pass.

STEP 2:
Calculation of rules (or) generalization of firing strengths:
The Second Layer

Firing strength means the degree to which an antecedent part of fuzzy rule is satisfied and it shapes the corresponding output function. The And logical operator is applied to obtain an output per rule. The product inference rule is used at fuzzification level to yield output values (O_i^2) at this level. The outputs at this node are labelled as $\prod$ as a result of multiplication of inputs from the layer one nodes.

$$O_i^2 = W_i \; = \mu_{A_i}\,(G) \times \; \mu_{B_i}\,(T) \qquad i = 1,2$$

The value of node output represents the strength of the rule.

STEP 3:
Calculation of the Ratio of Firing Strengths:
The Third Layer

The nodes in this layer are represented by circular nodes labeled N. The main objective of this step is to calculate the ratio of each rule's i^{th}firing strength to the sum of all rule's firing strength, which is also called as normalized firing strength with the output O_i^3 at this step

$$O_i^3 = \overline{W_i} = \frac{w_i}{\sum_i w_i} \qquad \text{where i= 1,2….9}$$

STEP 4:
Contribution of Each Rule:

The Fourth Layer Calculation of the contribution of each i^{th} rule towards the total output is O_i^4 formed at this step.

$$O_i^4 = \overline{W_i} f_i = \overline{W_i}(\,p_i T + q_i G + r_i) \quad \text{where i =1,2…9}$$

Where $\overline{W_i}$ is the output of layer 3 and p_i, q_i, r_i are consequent parameters which are updated on forward pass by least square estimates and are fixed in backward pass. This layer establishes the relation between weight based premise parameters and linear summation based consequent part of the adapted ANFIS structure.

STEP 5
Summation Step (Defuzzification Step):
The Fifth Layer

Each rule's fuzzy results are transformed into a crisp output O_i^5 at this step. The single output node in this layer sums up all the outputs of the previous layer as the output of ANFIS in this case is the duty cycle which is the switching pulses to boost converter.

$$K_p = \sum_i \overline{W_i}\; f_i = \left(\frac{\sum_i w_i f_i}{\sum_i w_i}\right) \text{where i= 1, 2…..9}$$

ANFIS FOR MPPT TRACKING

To validate the proposed control scheme, the simulated model is developed in Matlab/Simulink for the whole system. The Matlab ANFIS editor was used to create, train, and test a Sugeno type fuzzy system. The training data were loaded first to the editor. These data have a matrix form in order to be usable by the ANFIS editor. This matrix contains three columns. The first two columns contain the input data and the last column contains the output data (Duty cycle). After that, an initial FIS model was generated. This FIS was then trained using the hybrid optimization method which combines the least squares method and back propagation gradient descent method. The generated ANFIS model was imported to the Simulink fuzzy block to validate it [9].

The PV cell voltage varies from to 53 V and the current varies from 0.7 A to 5.9 A . By varying these two factors a set of data is generated in simulation. Twenty five of obtained data are then used to train the ANFIS network for the purpose of MPPT. The training is done offline using Matlab tool box. The overall neuro-fuzzy structure shown in Fig. 5 is a five-layer network.

The structure shows two inputs of the solar voltage and the current, which is translated into appropriate membership functions, three functions for voltage and three functions for current. These membership functions are generated by the ANFIS controller based on the prior knowledge obtained from the training data set. They are termed as "low," "medium," and "high." The common intersection areas between the low and medium solar voltage and the low and high voltage are nearly 75% and 50% respectively .

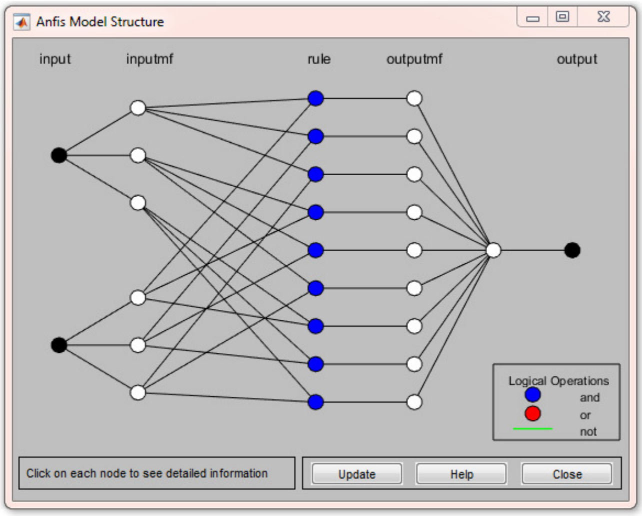

Fig.5 Five layer network Structure of Anfis

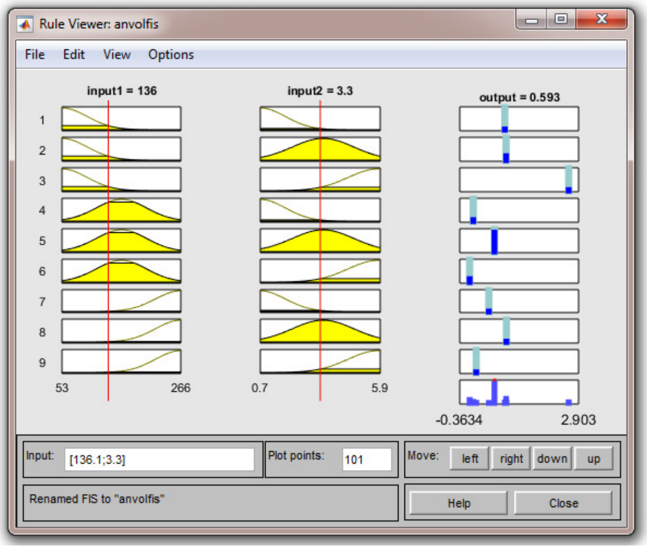

Fig. 6 Rule base of Anfis controller

The common intersection domain between the medium and high voltage is nearly 80%. In the current membership function, the intersection between low and medium current is nearly 70% and almost no common area between low and high current.The fuzzy rules are depicted graphically and the corresponding duty cycle are shown in Fig.6

The rule base depicts the relationship and mapping between the input and output membership functions. One particular situation is shown in Fig. 8 when the voltage is at 136V and the current is 3.3A . By varying the slider on the figure, all the conditions can be accessed. It can be seen that the temperature varies from 53V to 266V, the current varies from 0.7 to 5.6A, and correspondingly, the duty cycle varies shown in the last column.

There are nine rules that can follow, and more filled cells means high values and the blank or less filled cells represents low values; e.g., rule 8 can be read as if current input is low (follow membership function "low,") and the voltage is medium (follow membership function "medium,") then the duty (output of ANFIS controller) is 1V. The rulers (the vertical red line) shown in the voltage and current can be moved to check the rules for other operating conditions. The proposed ANFIS-based MPPT is more stable and faster than the conventional method.

Output power compensation by CPG mode

In CPG mode PV voltage can be regulated at the left side of the MPP by reducing the PV power to a certain set point. When the PV power is below the set point (i.e., Ppv2 ≤ Plimit), the MPPT algorithm is employed in order to allow the PV power to reach the set point shown in Fig.6. However, once the PV power reaches and starts to exceed the set point (i.e., Ppv2 > Plimit), the PV voltage is continuously perturbed toward the left side of the MPP until the PV output power is equal to the setpoint [10] [11]

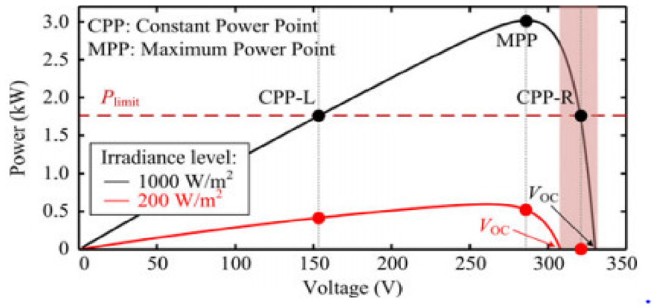

Fig.6 Operating points of PV system during CPG operation

The operating area of the CPG control is limited to be at the right side of the maximum power point (MPP) of the PV arrays (CPP-R) in Fig.7, due to the single-stage configuration. Unfortunately, this decreases the robustness of the control algorithm when the PV systems experience a fast decrease in the irradiance. A two-stage grid connected PV is employed to extend the operating area of the P&O-CPG algorithm. By regulating the PV output power at the left side of the MPP (CPP-L) , a stable CPG operation is always achieved, since the operating point will never "fall off the hill" during a fast decrease in irradiance.

DPC method dynamically changes the value of the set point P_{limit} during the operation in order to achieve the delta power control.

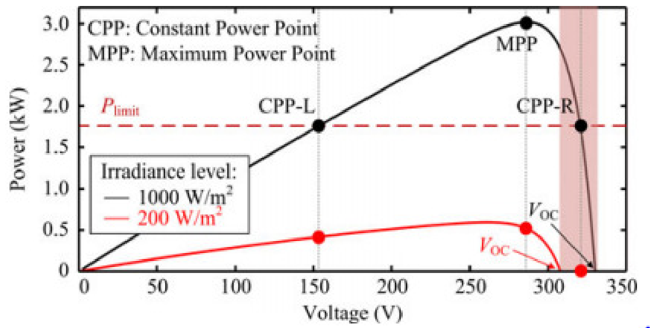

Fig.7 Operating principle of CPG scheme

Since the master PV string is operating in the MPPT mode with the extracted power , the PV power of the slave PV string Ppv2 has to be limited according to

$$P_{limit} = P_{pv1} - \Delta P$$

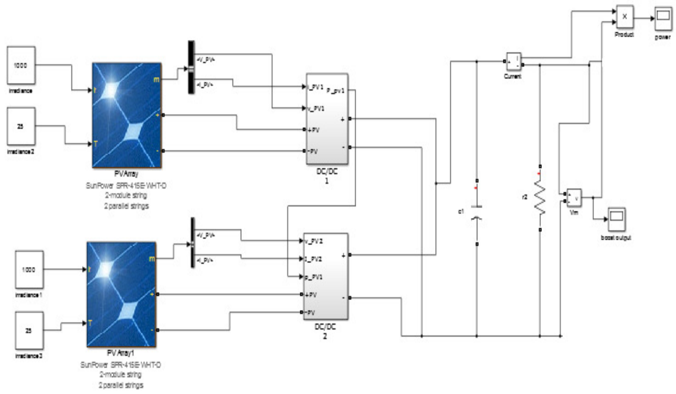

Fig. 8 Proposed Anfis based MPPT and CPG mode

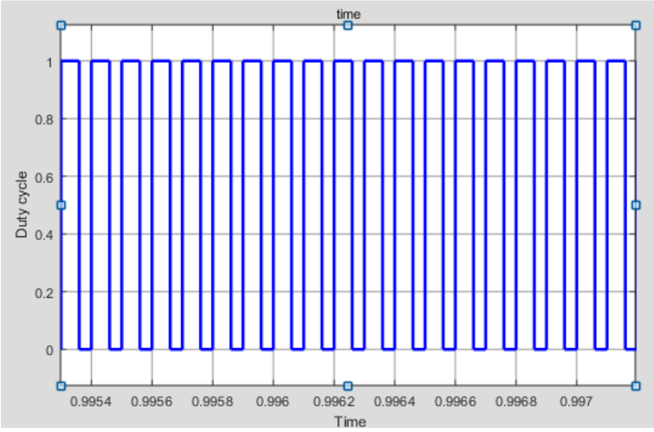

Fig. 9 Output pulses from Anfis

IV .GRID CONNECTED SYSTEM

In grid-connected PV applications, a two-stage conversion system, consisting of a dc–dc and a dc–ac conversion stages, is usually referred to as a multistring inverter configuration. Each PV string, consisting of several PV panels connected in series and/or parallel, is equipped with a dc–dc boost converter to step up the PV voltage Vpv to match the required dc-link voltage Vdc.

The boost converter also performs the active power control for each PV string individually. This gives a possibility to coordinate the active power control of each PV string in order to achieve the delta power constraint. Grid side converter, which is realized by full bridge topology, delivers the extracted PV power into ac grid by regulating the dc-link voltage to be constant through the control of the grid current Ig. In order to produce a pure sine wave output with low harmonics, an LCL-filter is used. The inverter output voltage can be utilized for grid integration [12].

V. SIMULATION RESULTS

The photovoltaic system simulated in MATLAB /Simulink. The PV module has the variable temperature and the irradiance. For analysis purpose,irradiance level of 1000W/m2 is considered. Fig.9 shows the anfis output which is change in duty cycle to boost converter. Fig .10 shows boost voltage of the converter for different irradiances. Fig.11 shows power variations with FLC control.

The 1.6-kW PV array specifications for one module are:

Number of series-connected cells	=	128
Open-circuit voltage: Voc	=	85.3 V
Short-circuit current: Isc	=	6.09 A
Voltage at maximum power point : Vmp	=	72.9 V,
Current at maximum power point Imp	=	5.58 A

When irradiance is 1000 W/m^2, boost voltage is 395V. When irradiance is 350W/m^2, boost voltage is 350 V. When irradiance is 500 W/m^2,boost voltage is 262V. The maximum power is tracked for various irradiance levels is obtained.

The PV output power is regulated according to the required amount of the power reserve by means of a constant power generation (CPG) strategy [13]. At the grid-side converter, the stored energy in the dc-link is also adaptively controlled to buffer the PV power increase during the MPPT operation, and thereby, keep the injected ac power to follow the required power reserve profile.

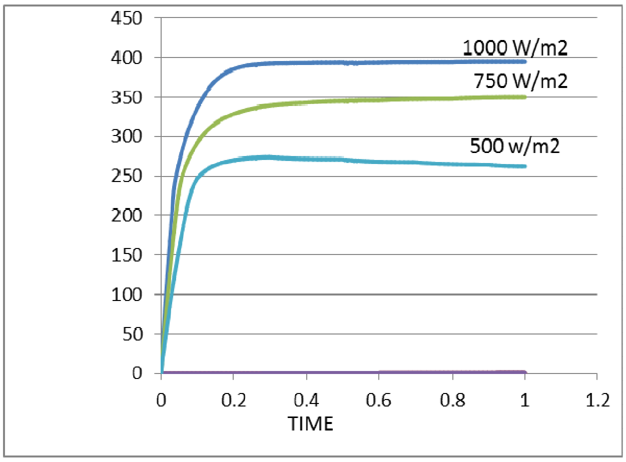

Fig.10 Boost voltage for different irradiance condition

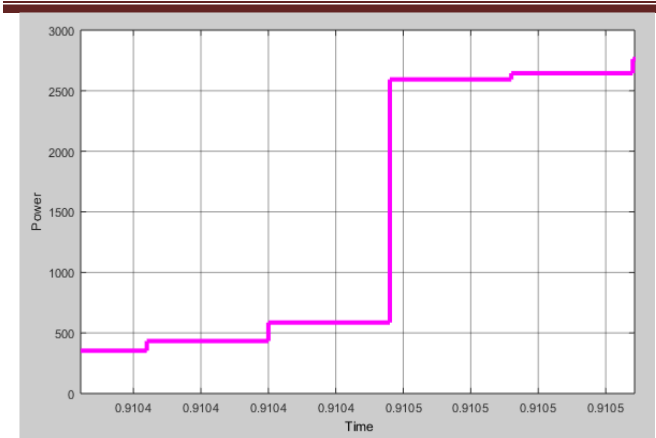

Fig.11 Power variations with Anfis control

VI .CONCLUSION

The performance of DPC with Anfis based MPPT and CPG mode is examined with temperature and solar iradiance through simulation. PV plant system can be given a reserve power margin and total P_{pv} active power is injected in to grid when PV system operates at unity power factor. Frequency of output AC voltage can be controlled by controlling the frequency of gate pulses.

ANFIS MPPT controller is developed in Matlab/Simulink in this paper. The proposed ANFIS can track the MPPT very fast and accurately even if the environment changes abruptly. The simulation results show that the ANFIS based MPPT method can quickly track the maximum power point (MPP) of the PV module at the transient state and shows better response with very less power oscillation around the MPP at steady state .

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