

Applying Fuzzy Learning Algorithm for MPPT in PV with Grid Connected System

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Abstract— Photovoltaic (PV) systems are being grid-connected via an interfacing converter which controlled to operate with Maximum Power Point Tracking (MPPT) to feed the grid by the maximum allowable solar energy. In this paper, A PV system is controlled using a adaptive and learning fuzzy controller technique to perform transferring the PV maximum power to the grid. The proposed technique applying Fuzzy Learning Algorithm for MPPT is applied to PV in Grid Connected mode. The learning mechanism has the ability to compensate for the changing parameters of the PV system due to environmental conditions. Moreover, the fuzzy controller reduces the noisy harmonics in the MPPT voltage and hence the inverter current. The system performance is investigated using a MATLAB simulation model.

Keywords— Modeling; PV; MPPT; adaptive and learning fuzzy controller;

I. INTRODUCTION

Demand of electrical power are growing rapidly. Seventy five percent of total global energy demand is supplied by the burning of fossil fuels. But increasing air pollution, global warming concerns, diminishing fossil fuels and their increasing cost have made it necessary to look towards renewable sources as a future energy solution. Since the past decade, there has been an enormous interest in many countries on renewable energy for power generation. The market liberalization and government's incentives have further accelerated the renewable energy sector growth[1].

An operating point of PV modules depends on what is connected to their terminals. In order to achieve maximal possible power from modules, maximum power point tracking (MPPT) is implemented in control of DC/DC converter connected to the PV modules. While changing duty cycle of PWM signal of the converter, the operating point of the system is being changed. The role of MPPT is to detect value of duty cycle for which PV modules generate maximum power [2].

Moreover, the methodologies that utilize both the datasheet and experimental data to extract the unknown parameters are also available in the literature [3]. The equivalent PV circuit is described by a set of transcendental equations, which are solved by iterative numerical procedures [4]. The closed-form solution of I-V characteristics can be obtained by utilizing the Lambert W function [4, 5]. A data-driven method based on the simple linear regression and smoothing spline

has been proposed in [6]. Fuzzy Logic controllers (FLC) [7] outperform conventional control techniques due to the following reasons: 1) Membership functions and inference mechanism inherited in their structure is able to present system nonlinearities more effectively; 2) They are independent on mathematical modeling and require only behavioral performance to set out linguistic variables and rule basis; and 3) They are better to present system uncertainties.

FLC with adaptive capabilities was developed by Procyk and Mamdani [8]. The parameters of the fuzzy controller are subjected to adaptation during system operation to meet a predefined performance under plant parameter variation. Fuzzy model reference learning control (FMRLC) [9, 10] uses reference models to describe the required performance to the adaptation mechanism. The term learning reflect the memorizing capability of the fuzzy controller where enhancement in the system performance can be experienced by frequent exposure of the system to the same dynamic range of state variables. The algorithm was successfully implemented to control the speed of induction motor drives [11, 12].

This paper introduces a novel maximum power point tracking MPPT the uses the control objective yet provide fast transient performance even in presence of variation in solar power radiation or temperature.

The paper is organized as follows: The second section introduces the structure of the proposed PV system. The third section presents fuzzy learning control algorithm. Section four discusses the simulation results. Finally, conclusion and future work are presented in section five.

II. STRUCTURE OF PV SYSTEM

The three phase multi stage grid connected system being modelled is shown in Fig. 1. It's consists of a PV array followed by step up stage feeding a current controlled voltage source inverter that feeds current into the three phase grid and local single phase loads.

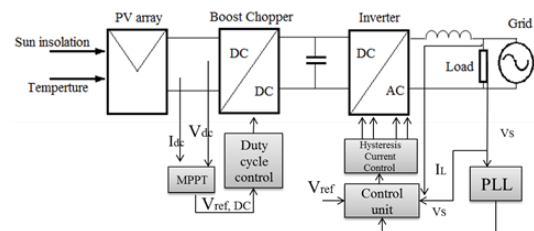


Fig. 1 The Overall system modelling including control signals

1- Current controller scheme

The well-known two-level current hysteresis band controller is suitable for this application and the most simple to implement in Matlab/Simulink environment. Fig. 2 (a), (b) shows two-level hysteresis band principle, and the obtained currents and voltage waveforms

The control variable for the DC-AC inverter is the RMS current reference $I_{RMS\ ref}$. The inverter output current is controlled so that it is in phase with the grid voltage and so that its RMS value equals the reference: $I_{RMS} = I_{RMS\ ref}$.

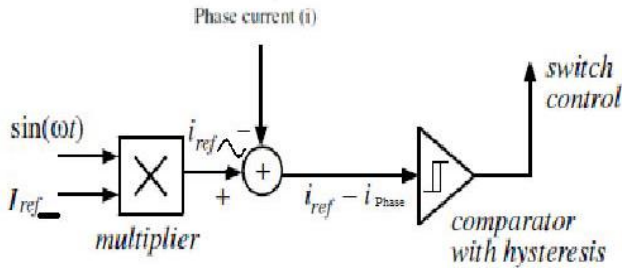


Fig.2 (a) Principle of hysteresis controller

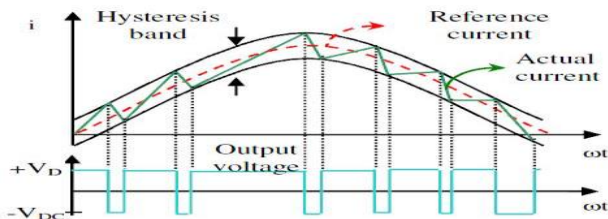


Fig.2 (b) Current and voltages waveforms

2- Control of the grid connected PV system

An LC filter is inserted after the dc-ac inverter in order to eliminate the harmonics contained in both the voltage and current of the inverter output. The task of the flyback boost DC/DC converter drains the power from the PV solar cell array and supplies the DC link capacitor with a maximum power point tracker obtained from the MPPT controller.

The main task of the grid connected photovoltaic system control system is to ensure frequency, phase and voltage RMS values are matching between the inverter output signals and grid signals.

III. FUZZY LEARNING CONTROL ALGORITHM

The structure of the adaptive and learning fuzzy controller is presented in figure (3). It consists of reference model that describes the required performance, the inverse model that represents the inverse dynamics of the system, the adaptation mechanism that modifies the rule-base at the main controller, and the main fuzzy controller. The reference model is the key for stable adaptation and control performance. An unachievable performance described by the reference model could lead to unstable adaptation and control performance. Hence, study of

system transients was conducted to set the parameters of the reference model.

The reference model is a disturbance rejection 2nd order system as shown in Fig. 2. Its forward transfer function is of type one to insure disturbance rejection with zero steady state error and is given by:

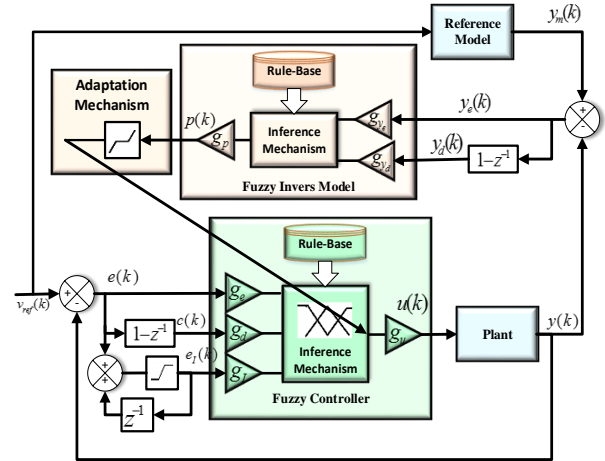


Fig. 3. FMRLC algorithm used for the control loop of SVC voltage regulator

$$\frac{Y_d(s)}{Y_m(s)} = \frac{\omega_n^2}{s(s + 2/\tau)} \quad (1)$$

where ω_n is calculated by the desired overshoot and τ as follow:

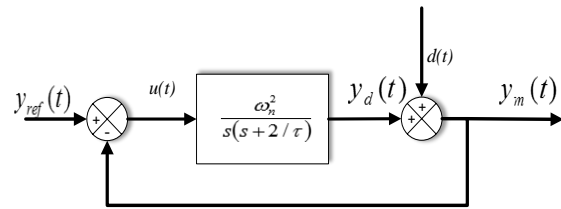


Fig. 4. Reference model

$$\omega_n = \frac{1}{\tau} \frac{\sqrt{\pi^2 + \ln^2(\%OS/100)}}{-\ln(\%OS/100)} \quad (2)$$

Table (1) Rule-base for the fuzzy Inverse model

y_d	NB	NE	ZE	PO	PB
NB	NB	NB	NB	NE	ZE
NE	NB	NB	NE	ZE	PO
ZE	NB	NE	ZE	PO	PB
PO	NE	ZE	PO	PB	PB
PB	ZE	PO	PB	PB	PB

NB: Negative big
 NE: Negative
 ZE: Zero
 PO: Positive
 PB: Positive big

The inverse model describes the inverse dynamics of the system for adequate inputs to the adaptation mechanism. However, due to the system complication,

a standard first order (PD) fuzzy system with rule-base set to default values, as shown in table (1), is adopted. The use of fuzzy structure inverse model reduces the sensitivity of mismatch between the actual system inverse dynamics and the one encoded in the fuzzy inverse model. It generates the required amount of control action that forces the system to follow the reference model. The inverse model has two inputs given by:

$$y_e(k) = y_m(k) - y(k) \quad (3)$$

$$y_d(k) = \left(\frac{y_e(k) - y_e(k-1)}{T} \right) \quad (4)$$

where y , y_m , y_e and y_d represent the output of the process, the output of reference model, the error between reference model output and process output, and the derivative of that error respectively. The learning and adaptation mechanism encodes the inverse model output into the rules at the rule-base of fuzzy controller. The fuzzy controller rules describe the nonlinear control surface that compensates and linearizes the overall system to match the reference model. The adaptation mechanism keeps adapting the control surface to compensate for time varying parameters. Triangular membership functions are used for fuzzy controller as shown in Fig. 4 where its centers b_i subjected to adaptation as follow:

$$b_i(k) = \begin{cases} b_{\min} & b_i(k-1) + \Delta b_i(k) \leq b_{\min} \\ b_i(k-1) + \Delta b_i(k) & b_{\min} < b_i(k-1) + \Delta b_i(k) < b_{\max} \\ b_{\max} & b_i(k-1) + \Delta b_i(k) \geq b_{\max} \end{cases} \quad (5)$$

$$\Delta b_i(k) = \eta g_p p(k)$$

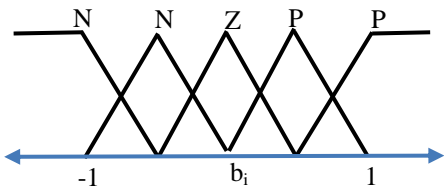


Fig. 5. Fuzzy controller membership functions

where, η is the learning factor, g_p is the adaptation gain, $p(k)$ is the output of the inverse model and b_{\min} and b_{\max} are the minimum and maximum control action values respectively. Both η and g_p can be combined as a one gain (g_p). The two limits values (b_{\min} and b_{\max}) are used to avoid generating control actions exceeding process input limits. Equation (6) shows that FMRLC algorithm provides both adaptation and learning capabilities. This is due to the fact that adaptation process is independent of inputs of the main fuzzy controller. In addition, adaptation process is seeking a certain performance defined by reference model regardless parameters change of the system.

A dead band was added to adaptation mechanism to avoid learning instability as follow:

$$b_i(k) = \begin{cases} b_i(k-1) + g_p p(k) & -p_{DB} \geq g_p p(k) \geq p_{DB} \\ b_i(k-1) & \text{otherwise} \end{cases} \quad (6)$$

where p_{DB} is the dead band limit of the learning process where ηg_p is replaced by g_p in equation (7).

The main fuzzy controller is a PID type fuzzy controller has the following inputs:

$$e(k) = r(k) - y(k) \quad (7)$$

$$c(k) = \frac{e(k) - e(k-1)}{T} \quad (8)$$

$$e_i(k) = T \left(e(k) + \sum_{i=1}^{k-1} e(i) \right) \quad (9)$$

Where e , c , and e_i are the error between reference input r and the measured output y , its derivative and its integral respectively in the current sample k . The membership functions covers dynamic range interval $[-1, 1]$. The input-output scaling factors g_x are used to adjust the signals dynamic range to the dynamic range covered by controller membership functions (where x represents the label of the signal at which the gain is placed on).

In order to avoid large values from integral part during transient period, a limiter is added after digital integrator described by equation (10). Such large values (over the dynamic range of the proper signal) could cause slowdown of the controller performance. The limiter maximum and minimum values are set in order of magnitude of output signal dynamic range.

The activation level of rule primes is given by:

$$\mu_A^i = \min(\mu_{A_j}^1, \mu_{A_k}^2) \quad (10)$$

where i is the index of the rule, A_j is linguistic value for the input (center of the j^{th} input membership function i.e. A_0 = negative big, A_1 = negative ... etc), and finally, $\mu_{A_j}^1$ is membership value of 1st input A_j linguistic value.

IV. SIMULATION RESULTS DISCUSSION

In order to investigate the effectiveness of the proposed model and control algorithms of the three phase grid connected PV system, a group of simulations results has been presented using Simulation Power Systems of MATLAB / Simulink environment.

The system parameters are listed in table 2. And Fly-back transformer parameters are listed in table 3.

Table 2: system parameters

Symbol	Quantity	Values
P_{MPPT}	Rated power	199 W
V_{MPPT}	Rated voltage	26.3 V
I_{MPPT}	Rated current	7.6 A
V_{OC}	Open-circuit voltage	32.9 V
I_{SC}	Short-circuit current	8.21 A
N_s	Number of series cell	54
N_p	Number of parallel cell	1
N_{sm}	Number of series module	1
N_{pm}	Number of parallel module	1
C	Solar capacitor	4700 μ F
T_c	Atmospheric Temperature	25°C
G_N	Solar Irradiation	1000 W/m ²
V_s	Grid voltage in RMS	220 V
V_{DC}	DC reference voltage	312V
C_{DC}	Fly-back capacitor	3.6mF
L_s	Grid tied inductor	30mH
C_F	DC-bus capacitor	5 μ F
F_{SM}	Sampling frequency	5kHz
F_{SW}	Switching frequency	5kHz
F	Line frequency	50Hz

Table 3: Fly-back HF transformer parameters:

Quantity	Symbol	Values
Inductance	L_{boost}	28 μ H
DC resistance	DCR Primary	0.008 Ohms
DC resistance	DCR Secondary	0.472 Ohms
Self-Resonant Frequency	SRF	360 kHz
Saturation current	I_{sat}	10.5 A
Turns ratio	Pri:Sec	1:12

Fig.6 (a) & (b) represent the typical conventional system at constant irradiation. The irradiance is kept constant (1000 W/m²) during the control course, while the temperature was changed. As it can be noted the PV voltage is not able to track the MPPT voltage accurately and hence maximum power cannot be achieved using conventional control techniques.

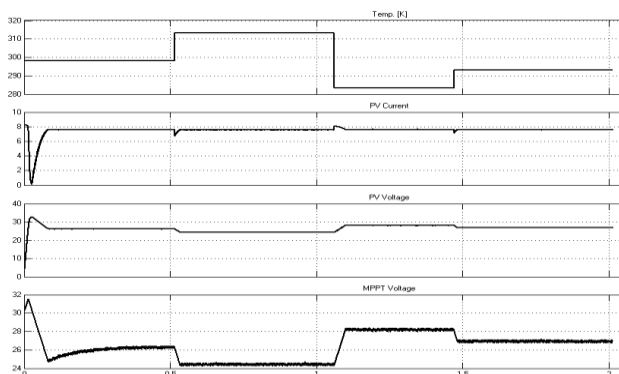


Fig.6 (a) Relation between temperature, PV current, PV voltage and voltage at MPPT at constant irradiation 1000W/m²

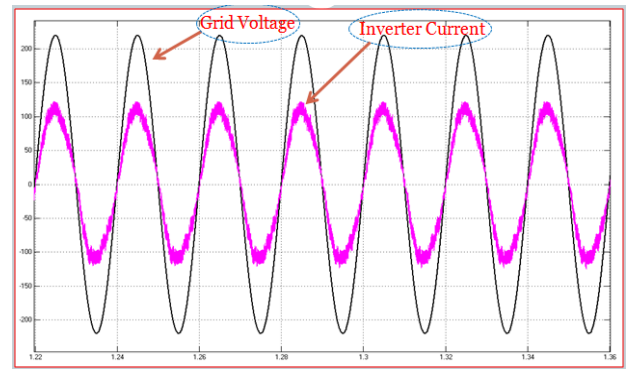


Fig.6 (b) Relation between. Invertercurrent and grid voltage

Fig. 7 shows the PV voltage in INC. COND. Method and using adaptive and learning fuzzy control algorithm at variable temperature conditions. As it can be noted the controller was able to produce the proper MPPT voltage is tracked perfectly by the PV voltage and hence a maximum power can be achieved at different operating condition. Moreover, the MPPT voltage is smooth with much reduced noise. This is a result of using fuzzy control algorithm that is less sensitive to uncertainty with capabilities of noise rejection.

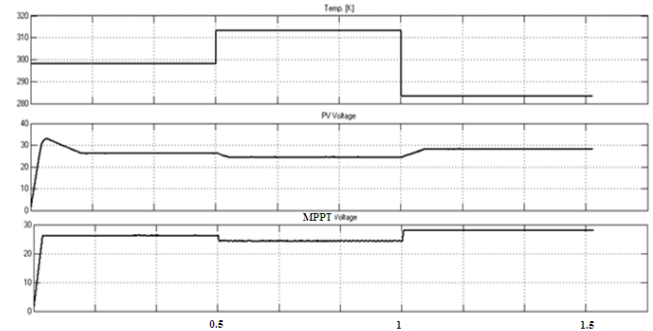


Fig.7 Relation between temperature, PV voltage in incremental conductance method PV voltage MPPT with adaptive Fuzzy at constant irradiation 1000W/m²

V. DISCUSSION

PV grid connected system has been modulated a number of parameters and considered in optimization to achieve maximum power generation. Applying MPPT algorithm resulted in an accurate PV model that more efficient system. Moreover the application of fuzzy control algorithm achieved the required synchronization to the grid and performed the power management between the system and the electrical grid.

Simulations for the PV system using conventional control technique and proposed adaptive fuzzy control algorithm have been conducted. The PV temperature was subjected to abrupt changes to investigate the controller capabilities of adaptation. The simulation results shows that the proposed fuzzy control algorithm outperform the conventional controller with the ability to track the MPPT trajectory with fast transient.

This study shows that the proposed control scheme offers a simple way to study the performance for utility

interface applications. It is simple to implement and capable of producing satisfactory sinusoidal current and voltage waveforms. To get better power quality, other control schemes for different inverter configurations and topologies are suggested.

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