PV-powered Water Pumping System (PVPS) matching improvement through Maximum Power Point Tracking (MPPT) by ANFIS Prediction

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***Abstract* –Adaptive Neuron-Fuzzy Inference System (ANFIS) based prediction for a linear correlation method to estimate the Maximum Power Point (MPP) of a stand-alone Photovoltaic Water Pumping System (PVPS) matching power improvement, has been investigated In this paper. Based on the previous experimental data collected under different environmental conditions of Ghardaia site, a statistical analysis method has been adopted by using both the open circuit voltage (Voc) and short circuit current (Isc) as input data for ANFIS. This method is used to classify the data in appropriate fuzzy membership functions (MFs). The fuzzyfied data will be used to test the ANFIS output with deduced appropriate rules to acquire a high precision of locating maximum voltage (Vmax) with few adaptation epochs. Through Matlab different selected ANFIS structure training, different RMSE (Root Mean Square Error) plots were obtained and compared. The comparison of the curves plotted upon the ANFIS output training (Vtmax) versus the experimental (Vemax), showed that the selected ANFIS structure deduced by the Gaussian Membership Function GMF (3X4) and GMF (4X3) are optimal. The application of the two last configurations has proved a good improvement in the system matching.**

***Keywords*— ANFIS, prediction, improvement, adaptation, training, membership function.**

I. Introduction

Since the solar irradiance varies quickly with time, the operating point of such load should meet quickly the maximum power extracted from photovoltaic array, that means the PV water pumping system directly coupled is usually requires maximum power point tracking (MPPT) controller [1].Many recent techniques have been developed and proposed to improve the PV cells maximum power point (MPP) matching system. The most recent used tracking techniques are: the Perturb and Observe (P&O) methods [2], the constant voltage method and the short-current pulse method. Recently, various intelligent approaches have been reported to estimate the PV array MPPT. The Intelligent controlling methods are widely used; they consist of the Artificial Neural Network (ANN) method [3]. The fuzzy logic Control (FLC) method [4] and Adaptive fuzzy logic control (AFLC) [5]. The Fuzzy Logic Controller (FLC) based method performs well under varying climate conditions (cell temperature and irradiance) [6]. In this context, efforts have been focused on the development of software as a yet simple and cost effective solution. The difficulties that face these methods are the rapid changes in solar radiation and the variety in cell temperature which affects the MPP setting. External sensors are used in many PV systems to measure solar radiation and ambient temperature to be used in approach estimation of the Maximum power point (MPP) as a function of measured data. In addition, the popular algorithms such as P&O and incremental conductance continue oscillation around the optimum operating point which causes power losses [7]. Moreover, these Algorithms may not give good results to the fast dynamic response and also it is very difficult to get an analytical expression in determining the optimum operating voltage for different solar cell technologies under changing weather conditions. The proposed method uses the advantages of Artificial Neural Networks (ANN) to predict the MPP voltage in time as a reference voltage for Fuzzy Logic Controller (FLC), known as Adaptive Neuron-Fuzzy Inference System (ANFIS) training. This approach is inspired from the (ANN) methods which were developed in the previous works [8]. The benefits of using (ANFIS) are that there are no requirements for knowledge on internal system parameters, less computational effort and provide a compact solution for multivariable problems. The acquired results may improve the MPP and reduce different oscillations round the operating point in such PV pumping system.

II. MPPT PREDICTION THROUGH ANFIS THEORY

A. *Description of the method*

The main purpose of such controlling techniques is the way of adjustment the duty cycle of the shunt MOSFET transistor of maximum power point tracking (MPPT) converter. The MPPT converter is used to maintain the PV array's operating point at the Maximum Power Point (MPP). The MPPT controller performs this by controlling the PV array's voltage or power independently of the load. The fuzzy controller introduced in uses dP/dI and its variations, as the inputs and computes MPPT converter duty cycle. The adaptive fuzzy tracker of MPPT considers variation of duty cycle, but it uses (dP/dV) and (dP/dI) to adapt duty cycle of the DC-DC converter. Many tracking control model have been proposed to overcome this problem. It is generally considered that a positive sign indicates power being delivered to the load and a negative sign indicates power being consumed by the solar cells. Taking into account the sign definitions as showed in the figure1.

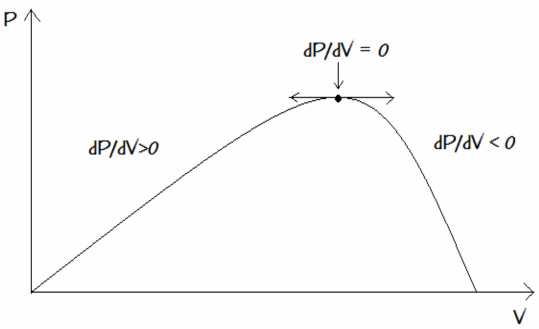

Fig.1 P-V curve different signs

B. *Adaptive Neuro-Fuzzy Inference System (ANFIS) structure*

It is necessary to know that the Adaptive Neuron-Fuzzy Inference System (ANFIS) [9], which is proposed by Jang (1993) is a multi-layer feed-forward neural network that combines ANN and fuzzy logic. Its main aim is to eliminate the basic problem in fuzzy system design, which defines the membership functions and designs fuzzy rules, by effectively using the learning capability of ANN for automatic fuzzy rule generation and parameter optimization (Nayak et al., 2004). Moreover, ANFIS not only maintains the mapping ability of ANNs but also possesses the advantages of fuzzy if-then rules for describing the local behaviour of such mapping and solving the highly non-linear control problem robustly. ANFIS has been widely studied and successfully applied to MPPT of PV water pumping control [10] and such as Chang (2006),

The Fuzzy Inference System (FIS) consists of three conceptual components: a rule base which contains a selection of fuzzy rules, a database which defines the membership functions (MF) used in the fuzzy rules and a reasoning mechanism, which performs the inference procedure upon the rules to derive an output. Neural network models are data based whereas fuzzy logic models are based on expert knowledge. The figure.2 illustrates the synoptic of the FIS.

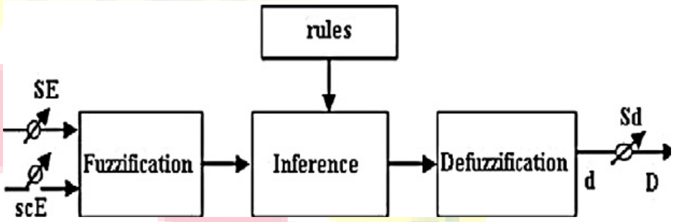

Fig.2 Fuzzy Inference System design

C. *ANFIS architecture methodology*

The ANFIS architecture methodology consists of five layers. The first layer consists of input nodes where each node corresponds to a linguistic label with a membership function (MF). In this study, a Gaussian bell-shaped G.BMF and a Gaussian GMF are used. The output of the first layer specifies the degree where the given input satisfies the MF. The second layer consists of rule nodes and the output of each node represents the firing strength of a rule. The node generates its output by multiplying all incoming signals involved in the rule. Therefore, the outputs of this layer are the products of the corresponding degrees from Layer 1. The third layer consists of average nodes that compute the ratio of each rule's firing strength to the sum of all rules'. The fourth layer consists of consequent nodes. The function of consequent nodes is to compute the contribution of each rule towards the total output. The fifth layer consists of output nodes. It includes a stable single node that sums up values of all signals to calculate the final output.

It should be noted that the number and shape of the membership functions of each fuzzy set as well as the fuzzy logic inference mechanism was initially selected based on trial-and-error methods, in a manner that the region of interest is covered appropriately by the input data.

The architecture of an ANFIS equivalent to a first-order Sugeno fuzzy model with two inputs and two rules is shown in the figure3.

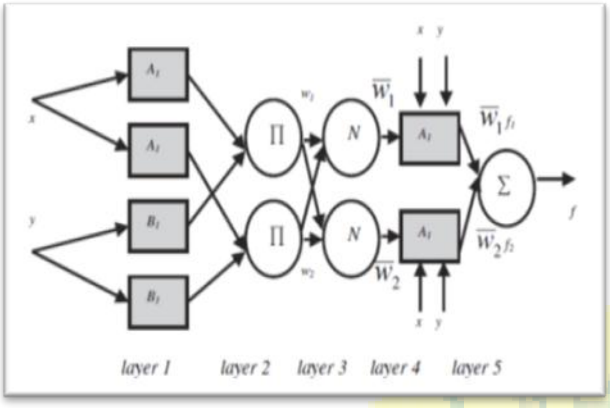

Fig. 3: Architecture of an ANFIS equivalent to a first-order.

1) Layer 1: consists of adaptive nodes that generate membership grades of linguistic labels based upon premise signals, using any appropriate parameterized membership function such as the generalized bell function.

$$O_1 = \mu_{Ai}(x) = \frac{1}{1+\left|\frac{x-c_i}{a_i}\right|^{2b_i}} \qquad (1)$$

Where, O1 is output, i is the output of the ith node in the first layer, x is the input to node i, Ai is a linguistic label (“small,” “large,” etc.) from fuzzy set A = (A1, A2, B1, B2,) associated with the node, and {ai, bi, ci} is the premise parameter set used to adjust the shape of the membership function.

2) Layer 2: In this layer the nodes are fixed nodes designated Π, which represent the firing strength of each rule. The output of each node is the fuzzy AND (product or MIN) of all the input signals;

$$O_{2i} = w_i = \mu A_i(x)\ \mu B_i(y) \qquad i = 1,2 \qquad (2)$$

3) Layer 3: The output of the layer 3 is the normalized firing strengths. Each node is a fixed rule labelled N. The output of the i^{th} node is the ratio of the i^{th} rule’s firing strength to the sum of all the rules firing strengths:

$$O_{3i} = \overline{w_i} = \frac{w_i}{w_1+w_2} \qquad i = 1,2 \qquad (3)$$

4) Layer 4: The adaptive nodes in the layer4 calculate the rule outputs based upon consequent parameters using the function:

$$O_{4i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \quad i = 1,2 \qquad (4)$$

Where, $\overline{w_i}$ is a normalized firing strength from layer 3, and (pi, qi, ri) is the consequent parameter set of the node.

5) Layer 5: The single node in layer.5 labelled P, calculates the overall ANFIS output from the sum of the node inputs:

$$O_{5i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad i = 1,2 \qquad (5)$$

II. THE ANFIS RAINING METHOD

The adaptive network based fuzzy inference system (ANFIS) is an adaptive network functionally equivalent to a first-order Sugeno fuzzy inference system. The ANFIS uses a hybrid-learning rule combining back-propagation gradient-descent and a least-squares algorithm to identify and optimize the Sugeno system’s signals. The equivalent ANFIS architecture of a first-order Sugeno fuzzy model with two rules is shown in Figure.3. The model has five layers and every node in a given layer has a similar function. The fuzzy IF-THEN rule set, in which the outputs are linear combinations of their inputs, is

Rule 1 : *if* x *is* A_1 *and* y *is* B_1 *then* $f_1 = p_1x+q_1x+r_1$
Rule 2 : *if* x *is* A_2 *and* y *is* B_2 *then* $f_2 = p_2x+q_2x+r_2$

Solar radiation, ambient temperature and wind speed are the main environmental factors that affect PV systems. Isc, Voc, Vmax and MPP are the main characteristics that specify the PV panels [11]. I-V curve characteristics and cell junction temperature of PV panels is adjusted due to any changes in environmental conditions. MPP changes due to irradiance level and cell junction temperature. Ambient temperature with current flows in PV cell increase the cell junction temperature. The temperature of cell junction is the main factor that reduces the maximum power output of PV panel [12].

III. MAIN RESULTS AND DISCUSSION WITH MATLAB SIMULATION

For a purpose to generate a Sugeno-type fuzzy inference system (FIS) structure Genfis1(Generate an FIS structure from data without data clustering) is used in Matlab toolbox to produce an FIS structure for an yearly experiment data of the PV generator (2 X 6) based on different proposed Gauss and

Generalized bell membership functions. The ANFIS model programmed in MATLAB is used to predict Vmax using Isc as a first input of ANFIS model and Voc as a second input. According to either reach to error criterion or the number off epochs setting in ANFIS function the input MFs parameters and output linear MFs of a Sugeno-type FIS structure is modified to reach best MFs that clustering input output data with minimum root mean square error (RMSE).

A. ANFIS Root Mean Square Error (RMSE) output

1) Gaussian bell Member ship function (GBMF): Six Gaussian Bell-shaped MFs models with a small number of rules (4x3) and minimum of epochs (between 150 and 300) has achieved minimum RMSE between (3.38% and 3.63%). The figure 4 shows the different RMSE issued plots and the global results are concluded in the table1.

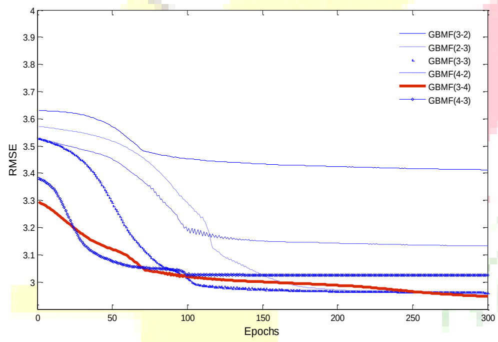

Fig.4: Different RMSE (%) for different G. Bell MFs

TABLE I
RMSE OF DIFFERENT G. BELL MEMBERSHIP FUNCTIONS

ANFIS INPUTS(G.BMF)	EPOCHS	RMSE(%)
GBMF(3x2)	250	3.63
GBMF(2x3)	250	3.58
GBMF(3x3)	250	3.53
GBMF(4x2)	280	3.5
GBMF(3x4)	300	3.3
GBMF(4x3)	150	3.38

2) Gaussian Member ship function (GMF): Six Gaussian MF models with small number of rules (4X3) and minimum of epochs (between 150 and 300) has achieved minimum RMSE (between 3.38% and 3.63%). The figure 5 shows the different RMSE issued plots and the global results are concluded in the table2.

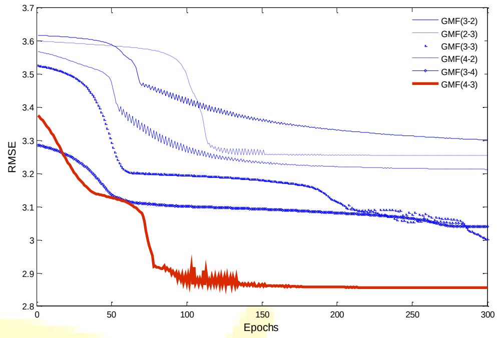

Fig.5 Different RMSE (%) for different GMFs

TABLE II
RMSE OF DIFFERENT G. MEMBERSHIP FUNCTIONS

ANFIS INPUTS (GMF)	EPOCHS	RMSE(%)
GMF(3x2)	300	3.62
GMF(2x3)	150	3.6
GMF(3x3)	220	3.57
GMF(4x2)	300	3.54
GMF(3x4)	280	3.28
GMF(4x3)	150	3.38

3) Selected ANFIS input: Through the mentioned tested models, the two selected Vmax RMSE obtained by GBMF (3x4) and GMF (4x3) inputs have been plotted in the figure 6. The optimal selected RMSE is that obtained through GMF(4x3).

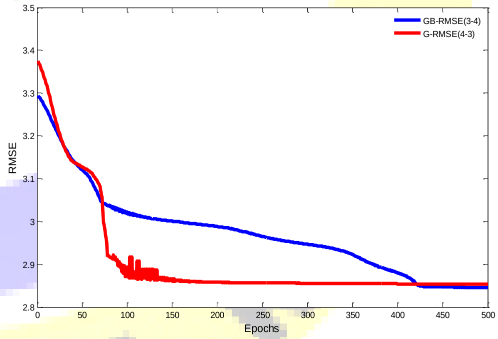

Fig.6: RMSE of both GBMF (3x4) and GMF (4,3)

B. Comparison of ANFIS output V_{max} and the experimental

The plots showed in the figures 7, 8, 9 and 10 illustrate the ANFIS output training (Vtmax) versus the experimental (Vemax), obtained for different training combination of the PV array I-V characteristics data collected through one year under outdoor conditions of Ghardaia. The ANFIS training has been performed for Gaussian Membership GMF (4x3).

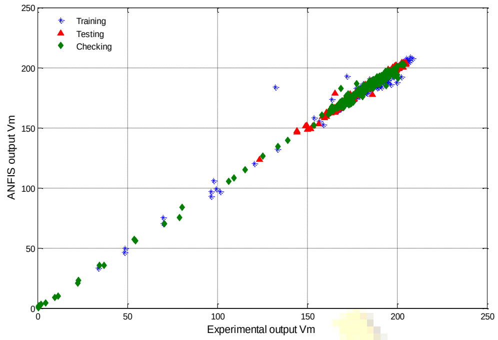

Figure 7. ANFIS (Vt_{max}) versus (Ve_{max})

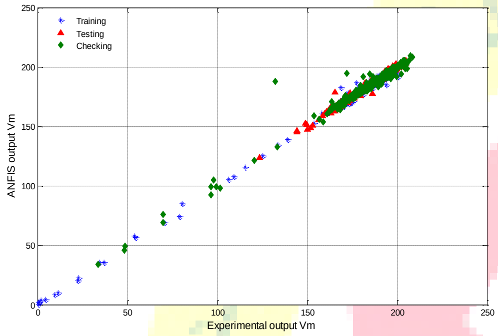

Figure 8. ANFIS (Vt_{max}) versus (Ve_{max})

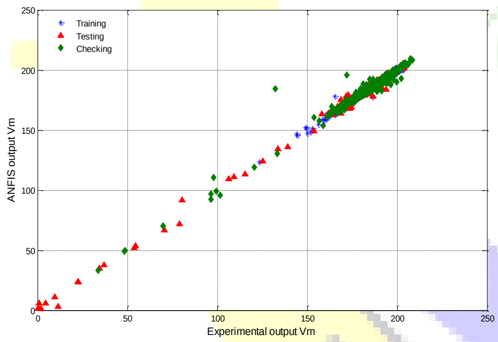

Figure 9. ANFIS (Vt_{max}) versus (Ve_{max})

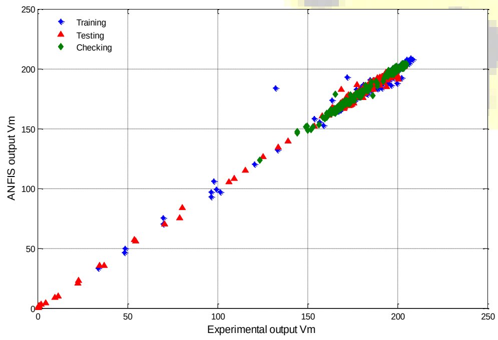

Figure 10. ANFIS (Vt_{max}) versus (Ve_{max})

The Figures.7, 8, 9 and 10 illustrate the ANFIS output (Vmax) versus the (Vmax) produced by the PV array. The ANFIS training used the same collected I-V characteristics data of the PV array. The curves show a very good linearity compared to different data training, testing and checking. In general, the ANFIS output changes after 150 epochs applying different schemes of inputs, through Gauss MFs or Bell-shaped MFs. The number of rules have been generated depends on the number of MFs, which is the product number of input.1 (current Isc) time MFs and the input.2 (open circuit voltage Voc) time MFs. Hence optimizing with minimum numbers of rules is very important in control system designed. Minimum error setting is associated with the system precision requirements. The analysis of the different results averred that the Gaussian Membership GMF(3X4) and GMF(4X3) based ANFIS structure is the most optimal appropriate training for the mentioned PV pumping system to locate the Maximum Power Point.

IV. CONCLUSION

A linear correlation method based on Adaptive Neuron-Fuzzy Inference System (ANFIS) to estimate the Maximum Power Point (MPP) of a stand-alone Photovoltaic Water Pumping System (PVPS) has been investigated. The important aim has to improve the system matching power load. Represented by the Membership Function's MF, the short circuit current (I_{sc}) and the open circuit voltage (V_{oc}) are selected as the inputs of the ANFIS. From the I-V PV array characteristics data base, the ANFIS training has been investigated and then the curves produced by the ANFIS output (V_{max}) versus the experimental (V_{max}) were plotted. The comparison of different obtained plots issued from training, testing and checking averred a very good linearity. The corresponding RMSE curves changed to constant line after 150 epochs applying different structures of inputs, through Gaussian Membership Functions (GMFs) and Gaussian Bell-shaped Membership Functions (G.BMFs). The trained V_{max} value showed an important amelioration, compared to the V_{max} recorded on the PV array output. The track of the Maximum Power point (MPP) by using ANFIS prediction is now possible to improve the overall PV pumping system efficiency.

The experimental results showed that the PV system with MPPT always tracks the peak power point of the PV module under various operating conditions. The MPPT not only increases the power from the PV module to the load, but also maintains longer operating periods for the PV system.

V. REFERENCES

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