An ANFIS-based Modeling for a Photovoltaic Power Supply (PVPS) System

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Abstract

Due to the increasing need for intelligent systems, the Adaptive Neuro-fuzzy Inference System (ANFIS) has recently attracted the attention of researchers in various scientific and engineering areas. The purpose of this work is to present the modeling of a Photovoltaic Power Supply PVPS-system using an ANFIS. For the modeling of the PVPS-system, it is required to find suitable models for its different components (ANFIS-PV-array, ANFIS-battery and ANFIS-regulator) under variable climatic conditions. A database of measured weather data (global radiation and temperature) and electrical signals (photovoltaic, battery and regulator voltage and current) of a PVPS system installed in Tahifet (south of Algeria) has been recorded for the period from 1992 to 1997 using a data acquisition system. These data have been used for the modeling and simulation of the PVPS-system. The ANFIS for the PV-array, battery and regulator have been trained by using 8 signals recorded from the different components of the PVPS system. Each signal is represented by 365*5 values (complete 5-years). A set of data for 4-years have been used for the training of the ANFIS, and data for 1-year has been used for the testing of the ANFIS. In this way, the ANFIS was trained to accept and handle a number of unusual cases. The comparison between actual and estimated values obtained from the ANFIS gave satisfactory results. The correlation coefficient between measured values and those estimated by the ANFIS gave good prediction accuracy of 98%. In addition, test results show that the ANFIS performed better than the neural networks. The results obtained from ANFIS can also be used for the prediction of the optimal configuration of PV systems, for the control of PV systems and for the prediction of the performance of the systems.

Keywords: Sizing PV system, Modeling, ANN, ANFIS

1. Introduction

The technology for power production from renewable energy sources is matured, available and reliable so the penetration of the technology depends mainly on the economic feasibility and the proper sizing of the components so as to avoid outages and ensure quality and continuity of supply. The modeling of PV power supply systems is the initial stage that must precede all sizing, identification or simulation applications. The PV systems are complex in their modeling. In literature, several models are proposed for modeling the different components of stand-alone PV systems based on analytical models or numerical simulations. Other methods are based on software simulation using readymade programs like Pspice, *Matlab-Simulink and Labview* [1-6]. Other more recent methods are based on fuzzy-logic inference for simulation of PV systems [7]. The main objective of this work is to investigate the suitability of artificial intelligence systems (neural networks and fuzzy-logic) for modeling and simulation of a stand-alone photovoltaic power supply (SAPVPS) system. It’s very difficult to determine an analytical or numerical model for SAPVPS system due to the variable climatic conditions which influence the system operation. However, we can consider the PV system as a non-linear system. Artificial Intelligent (AI) technique (neural networks, fuzzy logic, genetic algorithm, neuro-fuzzy,..) present a suitable solution for this kind of systems and can be used for modeling, prediction and optimization of complex systems. Possible applications are for:

- Sizing and analyzing the performance of SAPVPS systems [8-11].
- Control of maximum power point tracker MPPT [12, 13] in order to deliver the maximum energy from the PV-array.
- Prediction of the optimal configuration (PV-array and battery sizing) of PVS systems for the next day based on simulated data of PVPS-system [14].

This paper deals with the modeling and simulation of a PVPS-system using an adaptive Neuro-Fuzzy Inference System (ANFIS) under different climatic condition and to improve the results obtained in [15, 16]. Next section presents a description of stand-alone PV power supply system. Section 3 provides details of the ANFIS used in this study whereas the developed model used for the simulation of PVPS-system is presented in section 4. The results of the various simulations and validation of the results are presented in the final section.

2. Stand-Alone Photovoltaic System

A simple configuration of PVPS-system, which is the subject of this study, is shown in Fig. 1. The system is installed in Tahifet, Algeria (latitude 22°, longitude 6°, altitude 1400m) [17].

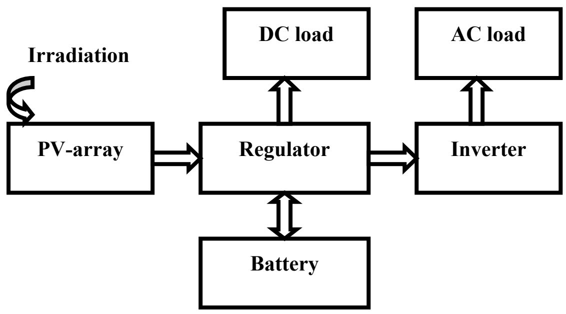

Fig. 1. PVPS-system schematic

Figure 2 shows the different signals recorded from the data-acquisition system. These signals are: PV array current (I_{pv}), battery voltage (V_b), PV array voltage (V_{pv}), ambient temperature (T_a), used current (I_u) and voltage (V_u), total solar irradiation (H) and the current of the battery (I_{rb}).

3. Adaptive neuro-fuzzy modelling

Neuro-fuzzy modelling [22, 23] refers to the way of applying various learning techniques developed in the neural network literature to fuzzy modelling or to a fuzzy inference system (FIS). The basic structure of a 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 (see Fig. 3).

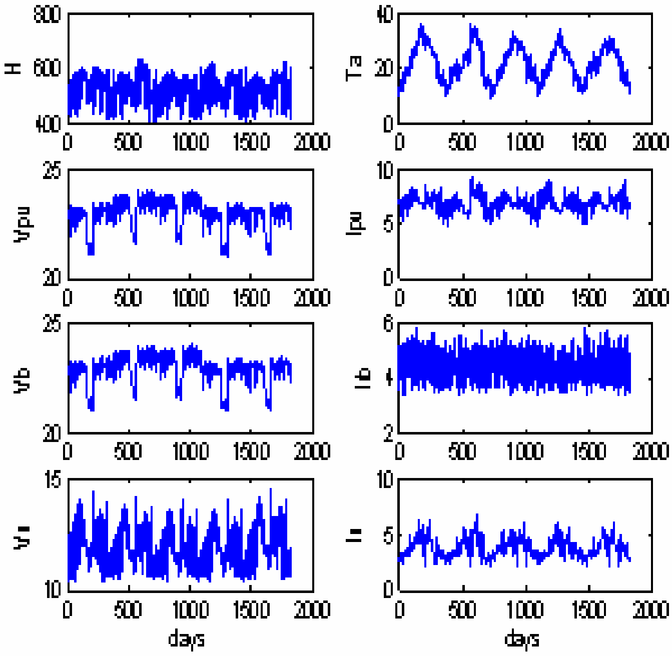

Fig. 2 Different signals recorded from data-acquisition of the PVPS-system

Neural network models are data based whereas fuzzy logic models are based on expert knowledge; in a situation in which both data and knowledge of the underlying system are available, a neuro-fuzzy approach is able to exploit both sources. The neuro-fuzzy system used here is the adaptive network-based fuzzy inference system (ANFIS). The system is an adaptive network functionally equivalent to a first-order Sugeno fuzzy inference system. The ANFIS uses a hybrid-learning rule combining backpropagation, 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 Fig. 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:

Rule1: *if* x *is* A_1 *and* y *is* B_1 *then* $f_1{:}=p_1x+q_1x+r_1$

Rule2: *if* x *is* A_2 *and* y *is* B_2 *then* $f_2{:}=p_2x+q_2x+r_2$

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 given by:

$$O_{1i} = \mu_{A_i}(x) = \frac{1}{1 + \left| \frac{x - c_i}{a_i} \right|^{2b_i}} \quad (1)$$

where output $O_{1,i}$ is the output of the i^{th} node in the first layer, x is the input to node i, A_i is a linguistic label ("small," "large," etc.) from fuzzy set $A = (A_1, A_2, B_1, B_2,)$ associated with the node, and $\{a_i, b_i, c_i\}$ is the premise parameter set used to adjust the shape of the membership function.

The nodes in layer 2 are fixed nodes designated ∏, 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:

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

The outputs of layer 3 are 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:

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

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

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

where $\overline{w_i}$ is the normalized firing strength from layer 3 and (p_i, q_i, r_i) is the consequent parameter set of the node. The single node in layer 5, labelled ∑, calculates the overall ANFIS output from the sum of the node inputs:

$$O_{4,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (5)$$

Training the ANFIS is a two-pass process over a number of epochs. During each epoch, the node outputs are calculated up to layer 4. At layer 5, the consequent parameters are calculated using a least-squares regression method. The output of the ANFIS is calculated and the errors propagated back through the layers in order to determine the premise parameter (layer 1) updates.

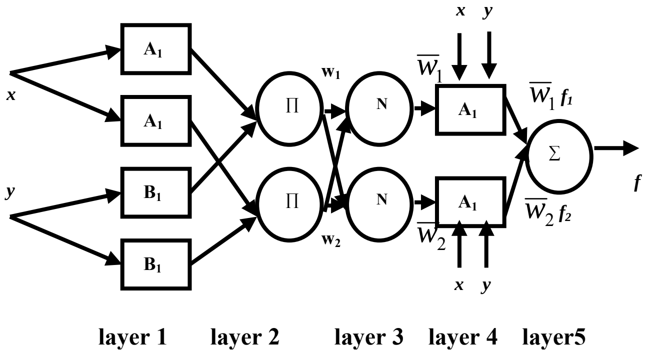

Fig. 3. Architecture of an ANFIS equivalent to a first-order *Sugeno* fuzzy model with two inputs and two rules

4. The developed model

The main objective of this work is to use the described ANFIS for modeling the different components of the PV-system (ANFIS-PV-array model, ANFIS-battery model and ANFIS-regulator model). A global model of PVPS-system is then developed which uses the different ANFIS models relative to each component of the PV-system. Signals recorded using the monitoring system presented in section 2 were used for training the various ANFIS models. Initially the various electrical signals used as input and output for each model (PV array, battery and regulator) are determined. A database of 365*5 patterns for each signal is divided in two parts, a dataset of 365*4 (4-years) patterns used for training the ANFIS and a dataset of 365*1 (1-year) patterns used for testing and validating the models. Before beginning the training of the each model the input and output for each model are fuzzified. The training algorithm used in this study is the Levenberg Marquardt. A soft computing program has been implemented for each ANFIS model (PV-array, battery, regulator and a global model) using Matlab (Ver.7). The block diagram of the developed model is shown in Fig. 4.

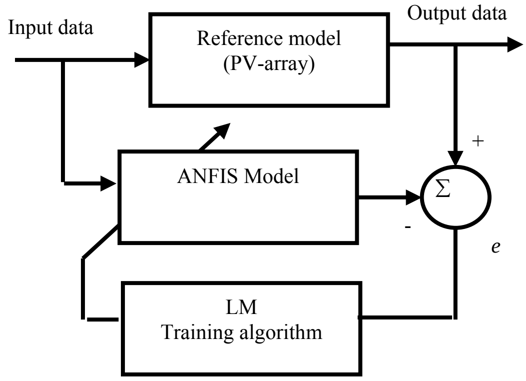

Fig. 4. Developed model

4.1. ANFIS-PV array model

The input signals of the ANN model for the PV array are the solar radiation (H) and ambient temperature (T_a). The output signals are the voltage (V_{pv}) and current (I_{pv}) of the PV array, from which energy provided by the PV array is estimated.

4.2. ANFIS-Battery model

The input signals of the ANN model for the battery pack are the ambient temperature (T_a) and the current coming from the regulator (I_{r_b}). The output signal is the battery voltage (V_b).

4.3. ANFIS-Regulator model

The regulator allows managing the transfer of energy through the load and the battery pack. The input signals for the ANFIS-regulator model are the battery current (I_{br}), and voltage and current of PV array (V_{pv}, I_{pv}). The output signals are the battery current (I_{rb}) and used current and voltage (I_u, V_u).

4.4 ANFIS global model

Figure 5 shows the architecture of the global model developed. This model combines the ANFIS-array model, ANFIS-battery model and ANFIS-regulator model linked in cascade. The purpose of the global model is to estimate and predict the current (I_u) and the voltage (V_u) used by the load by using as input only the solar irradiation (H) and ambient temperature (T_a).

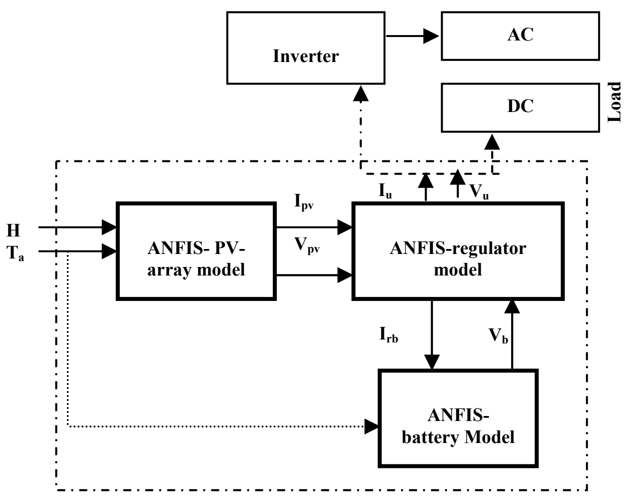

Fig. 5. Block diagram of developed global model

5. Simulation and validation

Initially, each model was trained separately and then the three models are combined in order to obtain the global model. The developed model can estimate the used current (I_u) and voltage (V_u) from only the ambient temperature (T_a) and irradiation (H). Also, all different signals for each component of the PVPS-system can be simulated. Figure 6 shows a comparaison between the different measured and simulated signals by the model. It should be noted that there is a very good agreement between all signals. Table 1 illustates the statistical test for the various measured and estimated signals of the PVPS-system. According to this table we note that the Mean Relative Error (MRE) varying between 4 and 6% which is satisfactory for this stage. Figure 7 presents the measured and predicted signals (I_u, V_u) by ANFIS for the global model. As can be seen a good accuracy is obtained. The coefficient of multiple determination R^2 is 98% which is satisfactory. In order to compare the performance of the ANFIS-models Fig. 8 is plotted which presents a comparison between different ANN-models for the output signals of the global model. As can be seen the ANFIS gives more accurate results.

The estimated electrical signals of the model developed can be used for:

- Studying the performance of PVPS-systems [10].
- Sizing and control of PVPS-systems [24].
- Predicting and reorganizing automatically the configuration of PVPS-systems [25].
- Filling missing data from databases (missing interval data can be recovered) [14].
- Control and optimization of the maximum power point tracker MPPT [11, 12], and
- Developing a new expert configuration of PVPS-systems [26,27].

6. Conclusion

In this paper an ANFIS has been used for the modeling of the different components of a PVPS-system and a global ANFIS model was developed to model the output signals (I_u, V_u) of the PVPS-system. The various components of the global model have been trained using data from the various input signals of the PVPS-system.

Table. 1 Statistical coefficient of measured and estimated signals of the SAPVPS system

Data	Mean	Training Error RMSE	Testing Error RMSE	MRE (%)
PV-array				
V_{pv}	13.89	0.0052	0.0095	0.510
$\widehat{V}_{pv}$	13.82			
Ipv	4.2574	0.0052	0.0095	0.712
$\widehat{I}_{pv}$	4.2271			
Battery				
Vb	25.01	0.0038	0.0041	0.451
$\widehat{V}_b$	24.96			
Regulator				
Vu	12.848	0.0025	0.0041	0.442
$\hat{V}_u$	12.889			
Iu	3.6626	0.0025	0.0041	0.645
$\widehat{I}_u$	3.7412			
Vb	25.012	0.0025	0.0041	0.071
$\widehat{V}_b$	24.965			
Global system				
Vu	12.848	0.0012	0.0019	0.368
$\hat{V}_u$	12.889			
Iu	3.7412	0.0012	0.0019	0.385
$\widehat{I}_u$	3.7541			

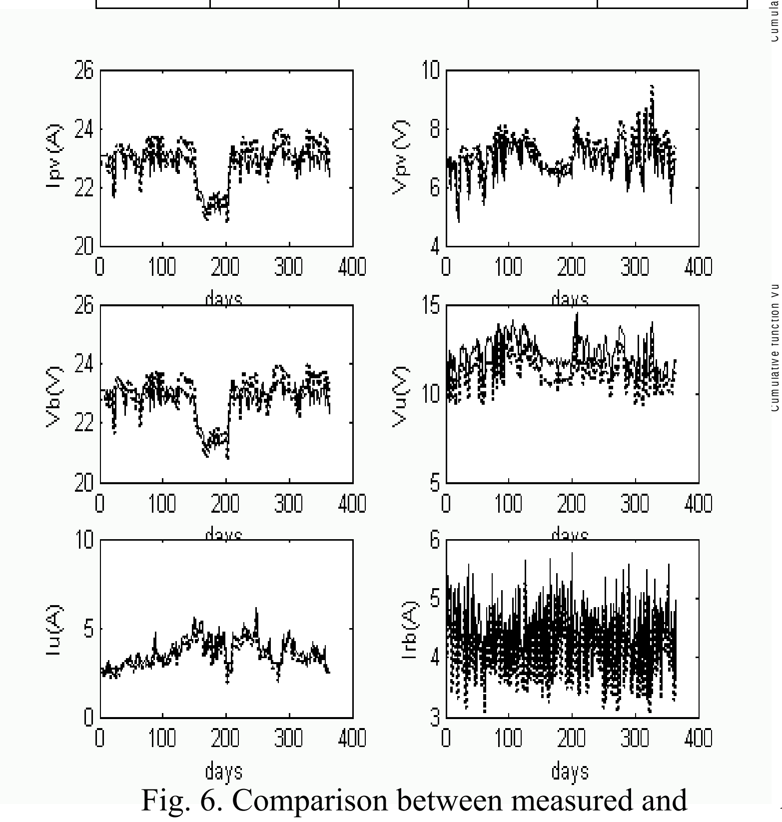

Fig. 6. Comparison between measured and estimated signals for each compound PVPS-system (__: measured; ...: predicted)

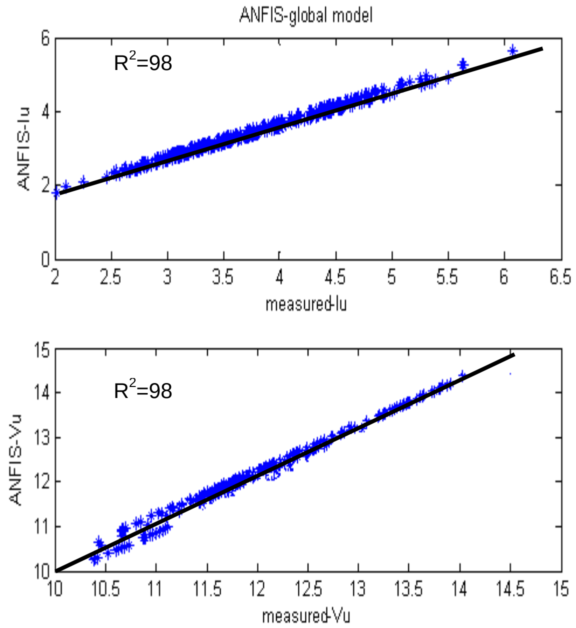

Fig. 7 Comparison between predicted ANFIS-global model and actual PVPS-system

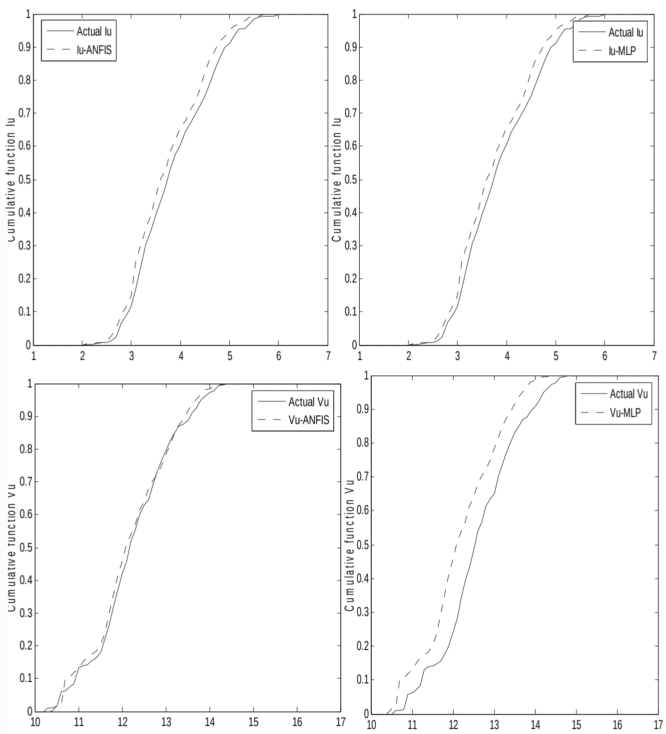

Fig. 8. A correlation coefficients between different ANN-architecture and ANFIS for the output signals of a global model (....: estimated: ____:actual)

A database of the input signals has been created from the experimental data-acquisition PVPS-system. The developed model can predict and simulate the different electrical signals of the

PVPS system from only the ambient temperature and solar irradiation. Results obtained indicate that a satisfactory accuracy is obtained between the measured and estimated electrical signals. The advantage of this model is that it needs as input only basic meteorological information for its operation. Existing numeric or analytic models reported in literature need several signals that are not always available or cannot easily be obtained. This methodology offers the possibility to implement an expert circuit that can be added to the PV system in order to control the PVPS-system and its signals. The results show that the ANFIS-model gives very accuracy results. In a future work we will include the control and optimization of PVPS-system using neural networks with a genetic algorithm.

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