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Daily energy planning of a household photovoltaic panel

Mohsen Ben Ammar [a,b], Maher Chaabene [a,*], Ahmed Elhajjaji [b]

[a] Unité de commande de machines et réseaux de puissance CMERP-ENIS-TUNISIA, Tunisia
[b] Laboratoire Modélisation, Information et Systèmes MIS-UPJV, Amiens, France

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ABSTRACT

This paper puts forward an energy planning approach which offers a daily optimum management of a household photovoltaic panel generation (PVG) without using storage equipment. The approach considers the PVG of the last 10 days to estimate the one of the next day, using a Neuro-Fuzzy algorithm. The estimated PVG is planned according to the consumer's needs so as to use the maximum of the generated energy. The algorithm decides by means of fuzzy rules the connection times of appliances, having different powers, to the photovoltaic panel (PVP) output during the day. The decision is made on the basis of optimization criteria with respect to different user operation modes. The approach is validated on a 260 Wp PVP and a set of four appliances of 30 W, 40 W, 60 W and 75 W. The system is installed at the National Engineering School, University of Sfax (ENIS) – Tunisia. The daily energetic assessment confirms that the PVG planning makes use of the estimated available energy in between 70% and 80%.

1. Introduction

The integration of renewable energy sources in installations where the electric grid is available requires a power management so as to ensure the user needs as when using only the electric grid. Furthermore, the management should bring maximum energy profit for the installation. Many strategies are developed so as to offer an energy management for installations using different source types: hybrid [1,2], wind [3], photovoltaic [4] and in different configurations: autonomous [5,6], isolated [7] and grid connected [7–9]. These researches use many tools as Fuzzy Logic [10,11], Genetic Algorithm [11,12], model based [13,14] and evolutionary algorithm [15].

The energetic effectiveness of PVP installation depends on the adequacy of the generated energy and the load demand. Since the PVP electric energy is allied to the availability of solar energy, some researches judge necessary the use of batteries so as to adapt load needs to PVP generation. However, batteries are costly and require continuous safeguarding. Hence, different approaches were adopted to avoid the use of batteries in photovoltaic applications such as pumping [16] and grid connected PVP [9]. Thus, the PVP represents the only source of electric energy for the installation which makes its operation depend only on the sun's appearance. In this field, research interests are essentially related to the modelling [17,18], the optimization [10] and the adaptation system of the PVP supply according to installation needs. Similarly, other researches are interested in grid connected PVP. Two types of installations are distinguished: either the PVP furnishes totally the generated energy to the grid which is the case of the large plants, or the PVP is used as a complementary source for an already grid connected installation. In the first design previous researches carried out deal generally with system assessment and characterization depending on site climate [10,19]. In the second pattern, researches developed energy management strategies so as to offer optimal function to photovoltaic plants where the grid is available [20]. Most of these researches are interested in a real time power management [21–23] giving an instantaneous decision on the way to consume the generated energy. The decision consists of selecting instantaneously the supply source (PVP or grid) for each appliance function of the available and the needed energies. Although, this kind of management offers a considerable energetic efficiency for the installation, it involves a high switching frequency of appliances connection between the electric grid and the PVP output which causes dysfunction essentially when appliances use memories or motors. This problem is due to the instability of the generated energy which is sensitive to the climatic perturbations.

To overcome this inconvenience, this paper proposes an energy planning of the estimated photovoltaic generation ($\widehat{PVG}_d$) for the next day. The approach considers the PVG during the last ten days in order to forecast its behaviour for the following day using a Neuro Fuzzy estimator ANFIS. Forecasted $\widehat{PVG}_d$ is optimally planned to provide energy to appliances of a household installation. Planning consists of fuzzy rules which determine, according to different operation modes, the connection times and operation periods of the household appliances to PVP output considering their nominal powers, the forecasted $\widehat{PVG}_d$ and some optimization

* Corresponding author.
E-mail address: maherchaabane@yahoo.com (M. Chaabene).

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criteria. The planning algorithm is implemented and tested using an installation located at *the National Engineering School, University of Sfax (ENIS) – Tunisia*. The approach assessment is shown over energetic audit.

Next, section two presents the PVG forecasting method. The planning algorithm is given in section three. Section four shows the obtained results and introduces a discussion. Finally, a conclusion is presented in section five.

2. PVP generation forecasting

The system's behaviour is estimated by either symbolic methods as fuzzy logic and decision trees [20], or adaptive methods using neural networks [24] and genetic algorithms [12]. Here, the two methods are combined so as to estimate the PVP generation. The approach consists of a Takagi and Sugeno model which uses fuzzy inputs and rules so as to provide a powerful tool for modelling complex non-linear problems when combined with a network structure called ANFIS: "Adaptive Network Fuzzy Inference System". ANFIS can be applied to non-linear forecasting where previous samples are used to forecast the sample ahead.

2.1. Fundamentals of the forecasting method

ANFIS is a class of adaptive multi-layer feed-forward networks. It generates fuzzy rules from an input–output data set. A typical fuzzy rule in a Takagi and Sugeno fuzzy model has the format [25,26]:

If x is A and y is B then $z = f(x, y)$

where A and B are fuzzy sets in the antecedent; $z = f(x, y)$ takes usually a polynomial form. Consider a model that contains two rules:

$$\text{Rule 1}: \text{If } X \text{ is } A_1 \text{ and } Y \text{ is } B_1, \text{ then } f_1 = p_1x + q_1y + r_1$$
$$\text{Rule 2}: \text{If } X \text{ is } A_2 \text{ and } Y \text{ is } B_2, \text{ then } f_2 = p_2x + q_2y + r_2$$

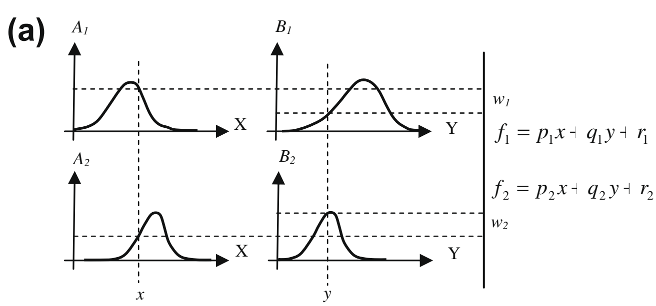

Fig. 1a. Takagi and Sugeno model.

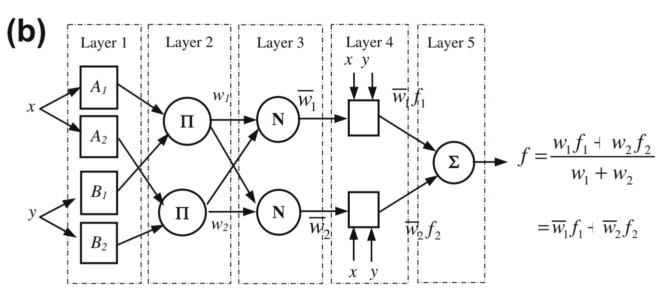

Fig. 1b. ANFIS architecture.

Fig. 1a illustrates graphically the fuzzy reasoning mechanism to derive an output f from a given input $[x, y]$. The firing strengths w_1 and w_2 are usually obtained as the product of the membership grades of the premise part, and the output f is the weighted average of each rule's output. Fig. 1b shows the corresponding ANFIS structure where nodes within the same layer perform functions of the same type. Note that O_i^j denotes the output of the ith node in jth layer [27,28].

ANFIS has, as the basic learning rule, the back-propagation gradient descent algorithm (the same used in feed-forward Neural Nets) which calculates the error signals recursively from the output layer backward to the input nodes. From this architecture, it is seen that given the values of premise parameters, the overall output function can be expressed as a linear combination of the consequent parameters [6,15]:

$$\begin{aligned} f &= \overline{w}_1 f_1 + \overline{w}_2 f_2 \\ &= (\overline{w}_1 x)p_1 + (\overline{w}_1 y)q_1 + (\overline{w}_1)r_1 + (\overline{w}_2 x)p_2 + (\overline{w}_2 y)q_2 + (\overline{w}_2)r_2 \end{aligned}$$

In time series estimation with ANFIS, two data sets are required so as to predict one step ahead: "training" and "test" data. Sub-clustering is used to generate ANFIS structure automatically. Training phase involves an iterative procedure, which seeks to calculate optimum values of system parameters by minimizing the sum of squared differences between model predictions and training data values. Once the training output model (f) is determined, a set of testing input–output data is applied to this model in order to compute the ANFIS prediction output. Time series analysis must content itself with estimating future output values by means of their own past values. The principle consists of using a time series, with a time step p, of n last measurements up to time t: $[m(t-(n-1)p), \ldots, m(t-p), m(t)]$ as training data and $[m(t-(n-2)p), \ldots, m(t), m(t+1)]$ as testing data, to estimate during a sliding time interval the p step ahead future values of the time series. $m(t+1)$ is fixed arbitrary at any value so as to achieve the ANFIS testing process. The retained output estimated value (p step ahead) is $\widetilde{m}(t+1)$ [29].

2.2. Application to PVG forecasting

During the training phase, the day is considered as time unit ($t = d - 1$: ending day), $p = 1$ (each day). Since the planning tool is essentially suitable during hot and moderate seasons where the climate is stable (as in cold season there is a lack of insolation,

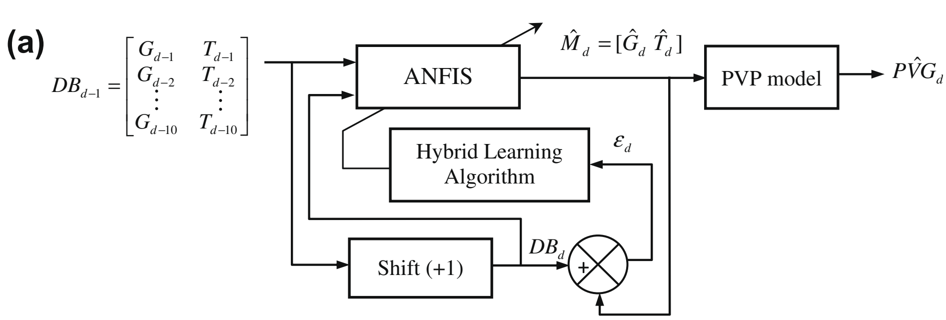

Fig. 2a. Neuro-Fuzzy estimator approach.