A novel maximum power point tracking method for PV systems using fuzzy cognitive networks (FCN)

A.D. Karlis\textsuperscript{a,}*, T.L. Kottas\textsuperscript{b}, Y.S. Boutalis\textsuperscript{b}

\textsuperscript{a} Electrical Machines Laboratory, Department of Electrical & Computer Engineering, Democritus University of Thrace, V. Sofias 12, 67100 Xanthi, Greece
\textsuperscript{b} Automatic Control Systems Laboratory, Department of Electrical & Computer Engineering, Democritus University of Thrace, V. Sofias 12, 67100 Xanthi, Greece

Received 7 September 2005; received in revised form 1 February 2006; accepted 15 March 2006
Available online 24 April 2006

Abstract

Maximum power point trackers (MPPTs) play an important role in photovoltaic (PV) power systems because they maximize the power output from a PV system for a given set of conditions, and therefore maximize the array efficiency. This paper presents a novel MPPT method based on fuzzy cognitive networks (FCN). The new method gives a good maximum power operation of any PV array under different conditions such as changing insolation and temperature. The numerical results show the effectiveness of the proposed algorithm.

© 2006 Elsevier B.V. All rights reserved.

Keywords: Photovoltaic systems; Maximum power point tracker; Fuzzy cognitive networks; Fuzzy cognitive maps

1. Introduction

It is well established that energy production and use based on consumption of fossil fuels can have deleterious environmental and human health impacts, including the potential for global warming of the earth through changes in the atmosphere’s concentration of carbon dioxide. Worldwide the conventional energy sources are rapidly depletioning, while population growth, increased expectations and means, and scientific and technological developments have dramatically increased the global demand for energy in its various forms. What this all implies is that the world is in the initial stages of an inevitable transition to a new energy system that, over time, will be less dependent on traditional uses of fossil fuels and increasingly dependent on renewable energy resources. In particular, solar photovoltaic (PV) energy is attracting a lot of attention, since it is clean, pollution-free, and inexhaustible. Applications of PV systems include water pumping, domestic and street lighting, electric vehicles, hybrid systems, military and space applications, refrigeration and vaccine storage, power plants, etc., all in either stand-alone or grid-connected configurations. A PV array is by nature a non-linear power source, which under constant uniform irradiance has a current–voltage ($I$–$V$) characteristic like that shown in Fig. 1. There is a unique point on the curve, called the maximum power point (MPP), at which the array operates with maximum efficiency and produces maximum output power. As it is well known, the MPP of a PV power generation system depends on array temperature, solar insolation, shading conditions and PV cells ageing, so it is necessary to constantly track the MPP of the solar array. A switch-mode power converter, called a maximum power point tracker (MPPT), can be used to maintain the PV array’s operating point at the MPP. The MPPT does this by controlling the PV array’s voltage or current independently of that of the load. If properly controlled by an MPPT algorithm, the MPPT can locate and track the MPP of the PV array. However, the location of the MPP in the $I$–$V$ plane is not known a priori. It must be located, either through model calculations or by a search algorithm. Fig. 2 shows a family of PV $I$–$V$ curves under increasing irradiance, but at constant temperature, and Fig. 3 shows $I$–$V$ curves at the same irradiance values, but at various temperatures. Needless to say there is a change in the array voltage at which the MPP occurs. For years, research has focused on various MPP control algorithms

\* Corresponding author. Tel.: +30 2541 079722; fax: +30 2541 079722.
E-mail addresses: akarlis@ee.duth.gr (A.D. Karlis), tkottas@ee.duth.gr (T.L. Kottas), ybout@ee.duth.gr (Y.S. Boutalis).
to draw the maximum power of the solar array. These techniques include look-up table methods using neural networks [1], perturbation and observation (P&O) methods [2,3] and computational methods [4]. One of the computational methods which have demonstrated fine performances under different environmental operating conditions is the fuzzy based MPPT technique [5,6]. The fuzzy theory based on fuzzy sets and fuzzy inference algorithms provides a general method of expressing linguistic rules so that they may be processed quickly by a computer. Recently the application of fuzzy control has been successful in photovoltaic applications. The fuzzy controller introduced in Ref. [5] uses $dP/dI$ and its variations $\Delta(dP/dI)$ as the inputs and computes MPPT converter duty cycle. The fuzzy tracker of Ref. [6] considers variation of duty cycle, but replaces $dP/dI$ by the variation of panel power. An on-line search algorithm that does not require the measurement of temperature and solar irradiation level is proposed in Ref. [7]. Other researchers analysed and compared the various MPPT techniques [4,8,9,10]. Beside that, in Ref. [8] a simple DSP-based MPPT algorithm is proposed while in Ref. [9] a combination of the modified constant voltage control and the incremental conductance method is introduced, showing good efficiency (especially in lower insolation intensity). In [10] an improved P&O method is proposed, where a three-point weight comparison method was developed to avoid the oscillation problem in the traditional P&O algorithm. Finally, in Refs. [11,12] efforts have been made to model the dynamic behaviour of a PV system in order to study its interaction with the pertinent MPPT system, while in Ref. [13] MPPT assessment and testing methods were presented in order to identify the accuracy, error and efficiency of the MPPTs.

This paper presents a novel MPPT method, which uses fuzzy cognitive networks (FCNs). FCNs [14,15] constitute an extension of the well-known fuzzy cognitive maps (FCMs) [16], so that they are able to operate in continuous interaction with the physical system they represent, while at the same time they keep tracking the various operational equilibrium points met by the system. FCNs can model dynamical complex systems that change with time following non-linear laws. They use a symbolic representation for the description and modeling of the system. In order to illustrate different aspects in the behavior of the system, a FCN is consisted of nodes with each node representing a characteristic of the system, including possible control actions. These nodes interact with each other showing the dynamics of the system under study. Moreover the FCN has the ability of continuous interaction with the physical system it represents sending control actions and receiving feedback from the system. The FCN integrates the accumulated experience and knowledge on the operation of the system, as a result of the method by which it is constructed, i.e., using human experts who know the operation.
of system and its behavior, but most significantly, it can adapt this knowledge based on the feedback from the physical system or by using appropriate training data.

In this paper a FCN is designed to solve the MPPT problem of a PV system. The nodes of the FCN represent essential operational (voltage, current and insolation, temperature) and control (current) variables of the PV system. The node interconnection weights are determined using data, which are constructed so that they cover the operation of a PV system under a wide range of different climatic conditions. The performance of the method is tested using climatic data for a specific PV system of the market, which reaches its MPP for various operational conditions, such as changing insolation and temperature and seasonal variations with great accuracy.

The paper is organized as follows. Section 2 presents mathematical relations between the essential variables of a PV system, which are necessary for simulating its operation under different insolation and temperature levels. Section 3 makes a brief introduction in fuzzy cognitive maps (FCMs), while Section 4 presents the graph of the proposed FCN to be used in conjunction with the PV system. Section 5 presents the essential parts of the operation of the FCN and Section 6 reports on the operation of the interconnected (FCN + PV) system based on climatic data. Finally, Section 7 concludes the work.

2. Simulation of the PV system

Using the equivalent circuit of a solar cell (Fig. 4) and the pertinent equations [8] the non-linear I-V characteristics of a solar array are extracted, neglecting the series resistance:

\[ I_0 = I_{ph} - I_{rs}(e^{V_0/kT_A} - 1) - \frac{V_0}{R_{sh}} \]  

where \( I_0 \) is the PV array output current (A), \( V_0 \) the PV array output voltage (V), \( q \) the charge of an electron, \( k \) the Boltzmann’s constant in J/K, \( A \) the p–n junction ideality factor, \( T \) the cell temperature (K), and \( I_{rs} \) is the cell reverse saturation current. The factor \( A \) in Eq. (1) determines the cell deviation from the ideal p–n junction characteristics. The ideal value ranges between 1 and 5 according to Ref. [9] and to a commercial available software package for PV systems PVSYST V3.1 (see Table 1).

The photocurrent \( I_{ph} \) depends on the solar radiation and the cell temperature as stated in the following equation:

\[ I_{ph} = (I_{scr} + k_i(T - T_r)) \frac{S}{100} \]  

where \( I_{scr} \) is the PV array short circuit current at reference temperature and radiation (A), \( k_i \) the short circuit current temperature coefficient \((A/K)\) and \( S \) is the solar radiation (mW/cm²).

The reverse saturation current \( I_{rs} \) varies with temperature according to the following equation:

\[ I_{rs} = I_{rs} \left( \frac{T_r}{T} \right)^3 e^{(1.115/kA)(1/T_r) - (1/T)} \]  

where \( T_r \) is the cell reference temperature, \( I_{rs} \) the reverse saturation current at \( T_r \), and \( k' \) is the Boltzmann’s constant in eV/K and the band-gap energy of the semiconductor used in the cell is equal to 1.115.

Finally, Eq. (4) was used in the computer simulations to obtain the open circuit voltage of the PV array:

\[ V_{oc} = \frac{AkT}{q} \ln \left( \frac{I_{ph} + I_{rs}}{I_{rs}} \right) \]  

From Eqs. (2)–(4) we get:

\[ I_{ph} = \frac{(I_{scr} + k_i(T - T_r))}{e^{V_{oc}/AkT} - 1} \]  

and from Eq. (1):

\[ R_{sh} = -\frac{V_{oc}}{I_{rs}(e^{V_{oc}/kT_A} - 1)} \]  

The required data for identifying the maximum operating point at any insolation level and temperature are the following:

- \( k_i \);
- open circuit voltage, \( V_{oc} \) (for initial conditions \( T_i = 25 \text{°C} \) and \( S = 100 \text{ mW/cm²} \));
- short circuit current, \( I_{scr} \) (for initial conditions \( T_i = 25 \text{°C} \) and \( S = 100 \text{ mW/cm²} \));
- maximum power voltage, \( V_{mp} \) (for initial conditions \( T_i = 25 \text{°C} \) and \( S = 100 \text{ mW/cm²} \));
- maximum power current, \( I_{mp} \) (for initial conditions \( T_i = 25 \text{°C} \) and \( S = 100 \text{ mW/cm²} \));

all given by the PV array manufacturer.

Table 1

<table>
<thead>
<tr>
<th>Technology</th>
<th>( A )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Si-mono</td>
<td>1.2</td>
</tr>
<tr>
<td>Si-poly</td>
<td>1.3</td>
</tr>
<tr>
<td>a-Si:H</td>
<td>1.8</td>
</tr>
<tr>
<td>a-Si:H tandem</td>
<td>3.3</td>
</tr>
<tr>
<td>a-Si:H triple</td>
<td>5</td>
</tr>
<tr>
<td>CdTe</td>
<td>1.5</td>
</tr>
<tr>
<td>CIS</td>
<td>1.5</td>
</tr>
<tr>
<td>AsGa</td>
<td>1.3</td>
</tr>
</tbody>
</table>

Fig. 4. Equivalent circuit of a solar cell.
3. Fuzzy cognitive maps representation and development

Fuzzy cognitive maps approach is a hybrid modeling methodology, exploiting characteristics of both fuzzy logic and neural networks theories and it may play an important role in the development of intelligent manufacturing systems. The utilization of existing knowledge and experience on the operation of complex systems is the core of this modeling approach. Experts develop fuzzy cognitive maps and they transform their knowledge in a dynamic cognitive map [17]. Fuzzy cognitive maps have already been used to model behavioral systems in many different scientific areas. For example, in political science [18], fuzzy cognitive maps have been used to model behavioral systems in many different scientific fields. Kosko enhanced the power of cognitive maps considering fuzzy values for their nodes and fuzzy degrees of interrelationships between nodes [22,23]. Fuzzy cognitive maps have been used for planning and making decisions in the field of international relations and political developments [19] and to model the behavior and reactions of virtual worlds. FCMs have been proposed as a generic system for decision analysis [20,24] and as coordinator of distributed cooperative agents.

The graphical illustration of FCM is a signed directed graph with feedback, consisting of nodes and weighted interconnections. Nodes of the graph stand for the nodes that are used to describe the behavior of the system and they are connected by signed and weighted arcs representing the causal relationships that exist among nodes (Fig. 5). Each node represents a characteristic of the system. In general it stands for states, variables, events, actions, goals, values, trends of the system which is modeled as an FCM [22]. Each node is characterized by a number $A_j$, which represents its value and it results from the transformation of the real value of the system’s variable, for which this node stands, in the interval $[0, 1]$. It must be mentioned that all the interconnection weight values belong to the interval $[-1, 1]$. With the graphical representation of the behavioral model of the system, it becomes clear which node of the system influences other nodes and in which degree.

The most essential part in modeling a system using FCMs, is the development of the fuzzy cognitive map itself, the determination of the nodes that best describe the system, the detection of the nodes that best describe the system, the direction and the grade of causality between nodes. The selection of the different factors of the system, which must be presented in the map, will be the result of a close-up on system’s operation behavior as been acquired by experts. Causality is another important part in the FCM design, it indicates whether a change in one variable causes change in another, and it must include the possible hidden causality that it could exist between several nodes. The most important element in describing the system is the determination of which node influences which other and in what degree. There are three possible types of causal relationships among nodes that express the type of influence from one node to the others. The weight of the interconnection between node $C_i$ and node $C_j$ denoted by $W_{ij}$, could be positive ($W_{ij} > 0$) for positive causality or negative ($W_{ij} < 0$) for negative causality or there is no relationship between node $C_i$ and node $C_j$, thus $W_{ij} = 0$.

The causal knowledge of the dynamic behavior of the system is stored in the structure of the map and in the interconnections that summarizes the correlation between cause and effect. The value of each node is influenced by the values of the connected nodes with the corresponding causal weights and by its previous value. So, the value $A_j$ for each node $C_j$ is calculated by the following rule [25]:

$$A_j^s = f \left( \sum_{i=1, i\neq j}^{N} A_i^{s-1} W_{ij} + A_j^{s-1} \right)$$  \hspace{1cm} (7)

where $A_j^s$ is the value of node $C_j$ at step $s$, $A_i^{s-1}$ the value of node $C_i$, at step $s - 1$, $A_j^{s-1}$ the value of node $C_j$ at step $s - 1$, and $W_{ij}$ is the weight of the interconnection between $C_i$ and $C_j$, and $f$ is a squashing function.

Squashing functions:

1. $f = \tanh(x)$ maps the nodes values in $[-1, 1]$;
2. $f = 1/(1 + e^{-cx})$ by using $c = 1$ we convert the nodes values in $[0, 1]$. It is also called sigmoid function. The second function is the most common function used in FCMs.

To account for the existence of steady nodes, Eq. (7) has to be slightly modified so that it does not provide with erroneous results [14]. Steady value nodes are the nodes that influence the remaining graph but they are not influenced by any other node of the graph. In this case, if the FCM convergence Eq. (7) is left to operate with weight adjustments that do not take into account the steady node values fact, then the equilibrium point will give node values for the above mentioned nodes, which might be different than the steady values, which in turn implies an unrealistic point of operation for our system.

![Fig. 5. A simple fuzzy cognitive map.](image)
Let us, for example, analyze an FCM having one or more nodes with constant values. This means that no human action can intervene, in a mechanic way with this value. In the graph of Fig. 6 nodes C1, C2 and C6 cannot change their values due to the influence of the other nodes. The values of these nodes derive from the system that is examined. The table of interconnection weights for this system is

\[
W = \begin{bmatrix}
0 & 0 & W_{13} & W_{14} & W_{15} & 0 \\
0 & 0 & W_{23} & W_{24} & W_{25} & 0 \\
0 & 0 & 0 & W_{34} & W_{35} & 0 \\
0 & 0 & W_{43} & 0 & W_{45} & 0 \\
0 & W_{53} & W_{54} & 0 & 0 & 0 \\
0 & 0 & W_{63} & W_{64} & W_{65} & 0
\end{bmatrix}
\]

We see that columns 1, 2 and 6 that concern nodes C1, C2 and C6 are zero. When applying Eq. (7) for node value updating we have to consider the steady values of nodes C1, C2 and C6 by using a companion adjusting equation. Thus, Eq. (7) is now replaced by the following two equations:

\[
A_{j}^{s,FCM} = f\left(\sum_{i=1, i\neq j}^{N} A_{i}^{s-1,FCM}W_{ij} + A_{j}^{s-1,FCM}\right) \quad (8)
\]

and for the steady state nodes the correction equation is

\[
A_{j}^{s,FCM} = A_{j}^{system} \quad (9)
\]

where \(A_{j}^{system}\) is the node’s value, derived from the physical system.

4. The fuzzy cognitive graph for the photovoltaic project

In this section we will propose an FCM design to represent the operation of a photovoltaic system. Our aim is to use the FCNs, which are extensions of FCMs and are presented in the next section, for estimating the maximum power point of the photovoltaic system. The graph shown in Fig. 6 represents a photovoltaic system, for a maximum power point Tracking use. The graph has six nodes, where nodes C1, C2 and C6 are steady value nodes and nodes C3, C4, C5 could be control nodes. In this approach, node C4 is the control node whose value is used to regulate the current of the system. The regulation of the current of the system means that a different power is now the output power of the photovoltaic. Control nodes are the nodes the values of which will be used to the real system as control actions. Node C6 is used to calculate the optimum current needed to regulate the output power of the photovoltaic in the maximum point. The nodes of the graph are related to the following physical quantities of the photovoltaic system.

Node C1 represents the irradiation with range in the interval [0, 1]. Zero is the minimum point of the irradiation (usually 0 mW/cm²) and one is the maximum point, corresponding to 100 mW/cm².

Node C2 represents the temperature which also must be in the interval [0, 1]. Zero is the minimum point of the temperature (usually 30°C) and one is the maximum point, usually 70°C.

Node C3 represents the optimum voltage of the photovoltaic system for the climatologic data obtained at the specific point of time, which also must be in the interval [0, 1]. Zero is the minimum point of the voltage (usually 0 V) and one is the maximum point \(V_{max}\), where \(V_{max}\) is calculated according to Eq. (4) by setting: \(T = T_{min}\) and \(S = S_{max}\).

Node C4 represents the optimum current of the photovoltaic system for the climatologic data obtained at the specific point of time, which also must be in the interval [0, 1]. Zero is the minimum point of the current (usually 0 A) and one is the maximum point \(I_{max}\), where \(I_{max}\) is calculated according to Eq. (2) by setting: \(T = T_{max}\) and \(S = S_{max}\).

Node C5 expresses the optimum output power of the photovoltaic system for the climatologic data obtained at the specific point of time, which also must be in the interval [0, 1]. Zero is the minimum point of the power (usually 0 W) and one is the maximum point \(W_{max}\), where \(W_{max}\) is a characteristic given from PV operational data under \(T_{min}\) and \(S_{max}\).

Node C6 is an artificial design node the value of which is used to regulate the equilibrium point in the nodes C3, C4 and C5. The value of C6 is steady and equals 1. The weights \(W_{63}\), \(W_{64}\) and \(W_{65}\) are originally set to zero and are allowed to change only when one or more weights affecting nodes 3, 4 and 5 exceed the value of absolute 1. For example the value of weight \(W_{63}\) is allowed to be updated when the weights that affect node C3 (\(W_{13}\), \(W_{43}\) and \(W_{53}\)) are going to take values larger from the absolute value 1. In this situation weight \(W_{63}\) is activated and its value is no longer set to 0. By using equilibrium node C6 and the weights connecting this node with nodes C3, C4 and C5, we manage to regulate the values of nodes C3, C4 and C5 by always keeping values of the graph weights below absolute value 1.

5. The fuzzy cognitive network approach for the photovoltaic project

Fuzzy cognitive networks (FCN) [14,15], constitute an extension of fuzzy cognitive maps. Unlike FCMs, which rely only on the use of the initially acquired experts’ knowledge about the
operation of the system and which is represented by the weights values of the map, FCNs may use these values only as a starting point or may not use them at all. The operation of FCNs is tightly connected with the operation of the physical system providing control values and taking feedback from the system. Moreover, during its initial training or its subsequent interaction with the physical system, the FCN keeps track of its previous equilibrium points by means of a collection of fuzzy if-then rules. Using these characteristics, the FCN becomes a dynamic control system. In this paper we use the FCN in close cooperation with a PV system as shown in Fig. 7. The FCN is first off-line trained by appropriately constructed data and then it is connected to any PV system to get feedback and send control values to regulate its output. Once the FCN is trained it is not further updated and acts as a non-adaptive controller of the PV system. The off-line training and the subsequent operation are described below.

5.1. Initial off-line training of the FCN

The off-line training is being performed in an incremental manner. This means that for each training data vector which contains PV value variables corresponding to different operation conditions, the FCN weights are updated to comply with the data vector. Moreover, this new acquired knowledge is been stored in a fuzzy-rule database. We can divide the training into two cooperating stages:

Stage 1: weight updating using new data

This stage is concerned with the method of updating the interconnections weights of FCN taking into account training data. Since the training is being performed incrementally, during stage 1, only one data vector is used. The FCN converges to its new weights values after a number of iterations. In each training iteration the FCN uses the updated weights to reach new equilibrium node values by means of Eqs. (8) and (9). These values are compared to the given training values and the error is given for the new updating iteration. The weight updating is made by using the following extended delta rule [14]:

\[
p = A^\text{system}_j - \frac{1}{1 + e^{-\left(\sum_{i=1, i \neq j}^{N} A^{\text{FCN}}_i W_{ij} + A^{\text{FCN}}_j\right)}}
\]

\[
W_{ij}^k = W_{ij}^{k-1} + R_{ij}(ap(1 - p)A^{\text{FCN}}_j)
\]

where \(p\) is the error, \(k\) the number of iteration, \(a\) the learning rate (usually \(a=0.1\)) and \(R_{ij}\) is a calibration variable, which prevents the FCN node and weight values from being driven in their saturation point. \(R_{ij}\) can be computed by the following formula [14]:

\[
R_{ij} = \eta \frac{\sum_{i=1}^{n} |W_{ij}|}{|W_{ij}|} \quad \text{if \hspace{1em} } W_{ij} \neq 0 \quad \text{and} \quad R_{ij} = 0 \quad \text{if \hspace{1em} } W_{ij} = 0
\]

where constant value \(\eta\) is used to drive values \(R_{ij}\) in the range \([0, 1]\). In most practical situations \(\eta=0.1\).

Stage 2: storage of the new knowledge in a fuzzy rule database

The procedure described in the previous stage modifies our knowledge about the system by continuously modifying the weight interconnections and consequently the node values. After the weight updating is taking place, the FCN reaches a new equilibrium point using Eqs. (8) and (9). Since a new training vector might produce different weights and different equilibrium point we have to keep track of the current knowledge (weights and equilibrium points) to be used after the training phase. We do
that by producing fuzzy if-then rules according to the following procedure [15].

Suppose, for example, that the FCN after being trained by a data vector converges to the following weight matrix:

\[
W = \begin{bmatrix}
0 & 0 & W_{13} & W_{14} & W_{15} & 0 \\
0 & 0 & W_{23} & W_{24} & W_{25} & 0 \\
0 & 0 & 0 & W_{34} & W_{35} & 0 \\
0 & 0 & W_{43} & 0 & W_{45} & 0 \\
0 & 0 & W_{53} & W_{54} & 0 & 0 \\
0 & 0 & W_{63} & W_{64} & W_{65} & 0 \\
\end{bmatrix}
\]

and concludes to an equilibrium point, which is:

\[
A = [A_1 \ A_2 \ A_3 \ A_4 \ A_5 \ A_6].
\]

Suppose also that for a new training data vector it concludes to a new equilibrium point:

\[
B = [B_1 \ B_2 \ B_3 \ B_4 \ B_5 \ B_6]
\]

with weight matrix:

\[
K = \begin{bmatrix}
0 & 0 & K_{13} & K_{14} & K_{15} & 0 \\
0 & 0 & K_{23} & K_{24} & K_{25} & 0 \\
0 & 0 & 0 & K_{34} & K_{35} & 0 \\
0 & 0 & K_{43} & 0 & K_{45} & 0 \\
0 & 0 & K_{53} & K_{54} & 0 & 0 \\
0 & 0 & K_{63} & K_{64} & K_{65} & 0 \\
\end{bmatrix}
\]

Based on the information obtained from the previous equilibrium points, a fuzzy rule based knowledge database is constructed. The database contains information about the shapes and ranges of the triangular membership functions of the involved variables (node values and weight values) and the fuzzy rules that associate these variables in each equilibrium point. This way, a new fuzzy if-then rule is constructed for each new equilibrium point. For example, the fuzzy rule database, which is obtained using the information from the two previous equilibrium points, is depicted in Figs. 8 and 9 and is resolved as follows.

There are two rules related to the above two different equilibrium situations:

- **Rule 1**
  - if node 1 is mf1 and node 2 is mf1 and node 3 is mf1 and node 4 is mf1 and node 5 is mf1 and node 6 is mf1
  - then w13 is mf1 and w14 is mf1 and w15 is mf1 and w23 is mf1 and w24 is mf1 and w25 is mf1 and w34 is mf1 and w35 is mf1 and w43 is mf1 and w45 is mf1 and w53 is mf1 and w54 is mf1 and w63 is mf1 and w64 is mf1 and w65 is mf1

- **Rule 2**
  - if node 1 is mf1 and node 2 is mf2 and node 3 is mf2 and node 4 is mf2 and node 5 is mf2 and node 6 is mf2
  - then w13 is mf2 and w14 is mf2 and w15 is mf2 and w23 is mf2 and w24 is mf2 and w25 is mf2 and w34 is mf2 and w35 is mf2 and w43 is mf2 and w45 is mf2 and w53 is mf2 and w54 is mf2 and w63 is mf2 and w64 is mf2 and w65 is mf2

The number and shape of the fuzzy membership functions of the variables of both sides of the rules are gradually modified as new desired equilibrium points appear to the system during its training. To add a new triangular membership function in the fuzzy description of a variable, the new value of the variable must differ from one already encountered value more than a specified threshold. Fig. 10 depicts this procedure. The initial value, \(a\), of the variable determines the pick of the triangular membership function (mf1) for the fuzzy description of the variable. When

![Fig. 8. Left-hand side (if part).](image-url)
Fig. 9. Right-hand side (then part).
a new value, \( b \), of the variable appears in a new equilibrium condition, it is compared with the previously encountered value \( a \). If \( |a - b| \) exceeds a specified threshold, \( c \), then a new triangular membership function (mf2) is created and the initial triangular function (mf1) is modified as shown in Fig. 10b. If \( |a - b| \) does not exceed the threshold the initial fuzzy partition of the variable remains unchanged (Fig. 10c). The threshold comes usually as a compromise between the maximum number of allowable rules and the detail in fuzzy representation of each variable.

Once the new knowledge has been stored using the above procedure we run again stage 1 using a new training vector. The procedure stops after all data vectors have been presented.

5.2. Control of a PV system using the trained FCN

Once the FCN is off-line trained it can be connected to the PV system according to Fig. 7. The FCN receives feedback from the PV system. The FCN weights, appropriate for these feedback values, are extracted by using the fuzzy rule database obtained during the training phase from stage 2. Using these weights the FCN reaches a new equilibrium point using Eqs. (8) and (9). The control node value of the FCN is then used to regulate the PV system in order to give maximum power for the current conditions.

6. Results

Needless to say that irradiation and temperature play the most significant role on the maximum power that is drawn from a PV module. In order to measure these two quantities a pyranometer and a thermocouple is often used, although the output from these two measuring devices is not always the most adequate information to identify the operating point yielding the maximum power, which is of course a drawback of this methodology. The short circuit current from the PV array gives the most adequate information of the effective insolation and temperature using Eqs. (1)–(6).

We construct training data for the FCN using the following procedure.

We use some typical climatic data. These data are chosen to be:

- Irradiation (S-node 1): we select values in the range of 0–100 mW/cm\(^2\) using a step of 2 mW/cm\(^2\).
- Temperature (T-node 2): we select values in the range of \(-30\)–70\(^\circ\)C using a step of 2\(^\circ\)C.

By using all the possible combinations of these data and by using the simulation of the photovoltaic array we calculate the values of the optimum voltage (node 3), current (node 4), and output power (node 5) from Eqs. (1)–(4). Using these node values for nodes 1–5 we update the weights of the FCN according to stage 1 of the training procedure and for the equilibrium point derived for any possible combination we store the knowledge according to stage 2.

The possible combinations of the climatic data are 2601 and the FCN creates 51 triangular fuzzy numbers for nodes 1 and 2, 47 for node 3, 89 for node 4, 64 for node 5, 13 for node 6. Also, 867 fuzzy if-then rules are created to store the knowledge. The number of rules appears to be large because it accounts for all possible combinations of climatic data, even for those which are unlikely ever to occur. It could be significantly reduced if we excluded this kind of combinations.

When we connect the FCN system to the PV-array the PV-array sends the values of nodes 1 and 2 and through the fuzzy rule database, we decide which weights values are appropriate to express the values of nodes 3, 4 and 5. Executing Eqs. (8) and (9) and using the weights derived above we calculate the new equilibrium point which expresses the values of the optimum current, voltage and output power of the PV-array for the climatic data obtained at the specific point of time. In the next step the FCN sends the values of the control nodes, to the PV-array controller thus determining the optimum current, which corre-
In order to evaluate the effectiveness of the proposed algorithm we used the trained FCN for controlling the operation of a BP270L PV array. The parameters of the PV array are given in Appendix A, where a sample of weight matrix and the corresponding equilibrium points are also given. The expected on-line measurements of the PV system's quantities (current, voltage, and short-circuit current), were simulated using both Eqs. (1)–(4) and real data of insolation and temperature over a period of one year. These data were also processed in order to find the less shiny and the shiniest days of the year. These two days (14 January 2002 and 09 July 2002) typical for winter and summer seasons, respectively, were selected, as they are the less and most optimistic cases respectively in order to evaluate the accuracy of the proposed method. Figs. 11 and 12 present comparisons between (a) evaluated and (b) achieved using FCN MPP of the PV array for the days mentioned above. The abbreviation $Wh$ shown in these figs stands for the total energy (measured in watt–hours) produced by the PV array during each one of these particular days of the year, while the error calculated for the same day is evaluated by the following equation:

$$\frac{Wh_{\text{evaluated}} - Wh_{\text{FCN}}}{Wh_{\text{evaluated}}}$$

where $Wh_{\text{evaluated}}$ is the total amount of energy evaluated for that day and $Wh_{\text{FCN}}$ is the total amount of energy expected for the same day by using the FCN method.

The same procedure was followed for two other typical days of spring and autumn respectively (08 April 2002 and 08 October 2002). The results are shown in Figs. 13 and 14, respectively. Finally we run the procedure for all the days of 2002. The average annual error of the method was estimated to be 2.01%. The range of daily errors was between 1.7 and 4%.

In order to highlight further the effectiveness of the proposed methodology it was compared to the well known MPPT algorithm of the P&O method, which was also simulated for the same case study. The results are very encouraging. For example, a 3 min, randomly depicted, sample shows in Fig. 15 that the...
Fig. 13. Comparison between (a) evaluated and (b) achieved using FCN MPP of the PV array for a day in spring of the year 2002.

Fig. 14. Comparison between (a) evaluated and (b) achieved using FCN MPP of the PV array for a day in autumn of the year 2002.

FCN method leads to less waste of energy compared to the P&O one. The evaluated error for each of these minutes is presented in Table 2. The total annual error for the year 2002 of the P&O method is estimated to be 6.609% which is much greater than the one of the FCN method (i.e. 2.01%), which was mentioned above.

A typical real life application of the proposed methodology would require the following steps:

(a) once a specific PV array is selected its parameters are entered to the computer;
(b) based on these parameters the training data are produced using the various combinations of the climatic data and Eqs. (1)–(4);
(c) the FCN is being trained using the above data and according to the procedure described in Section 5;

Table 2
Error between the theoretical and the estimated values of energy

<table>
<thead>
<tr>
<th>MPPT method</th>
<th>1st</th>
<th>2nd</th>
<th>3rd</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCN</td>
<td>2.5818%</td>
<td>3.0378%</td>
<td>0.1769%</td>
</tr>
<tr>
<td>P&amp;O</td>
<td>14.4914%</td>
<td>0.6209%</td>
<td>0.7717%</td>
</tr>
</tbody>
</table>
(d) once the FCN is trained is left to operate with the specific PV array.

It is evident that this procedure can be applied to any PV array of the market.

The control system may be implemented as a software embedded in a microcontroller. The control system will employ the FCN logic for maximum power point tracking. It should make simple current and voltage measurements on the PV array and produce control output as a reference signal for an AC/DC inverter or a DC/DC converter.

7. Conclusions

A novel MPPT method based on the fuzzy cognitive networks (FCNs) was proposed and investigated. FCNs can model dynamical complex systems that change with time following nonlinear laws. Moreover, they can operate in continuous interaction with the physical system they represent and adapt their knowledge based on training data. The efficiency of the proposed algorithm has been presented for identifying the maximum operating point for the real time MPPT control of PV modules. The FCN was off-line trained using appropriately constructed data. With this training the FCN is appropriate to operate with any PV system under changing climatic conditions. When tested with a specific PV system gave accurate predictions under different conditions such as changing insolation and temperature. The accuracy is not degraded due to seasonal variations.

Appendix A

A.1. PV system data

- \( k_t = 2.8 \) mA/°C;
- open circuit voltage, \( V_{oc} = 21.4 \) V;
- short circuit current, \( I_{sc} = 4.48 \) A;
- maximum power voltage, \( V_{mp} = 17.1 \) V;
- maximum power current, \( I_{mp} = 4.15 \) A.

Based on the node description presented in Section 4 and following the procedure described in Section 5 and by using the PV system data given by the manufacturer we can see, as an example, an equilibrium point with weight matrix:

\[
W = \begin{bmatrix}
0 & 0 & -0.0006 & 0.0962 & 0.0470 & 0 \\
0 & 0 & -0.0156 & -0.1528 & -0.0222 & 0 \\
0 & 0 & 0 & -0.0097 & -0.0242 & 0 \\
0 & 0 & -0.0041 & 0 & -0.0740 & 0 \\
0 & 0 & 0.0671 & 0.3654 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

and \( A \) vector is \( A = [0.8 \ 0.55 \ 0.6681 \ 0.7195 \ 0.6461 \ 1] \).

The \( A \) vector means that: \( S = 80 \) mW/cm\(^2\), \( T = 25 \) °C, \( V = 17 \) V, \( I = 3.3118 \) A and \( W = 56.301 \) W.

Dr. Athanassios D. Karlis (1967) received his Diploma in Engineering degree and Ph.D. from the Electrical and Computer Engineering Department of the Aristotle University of Thessaloniki, Greece, in 1991 and 1996, respectively. He is currently Lecturer at the Electrical Machines Laboratory of the Department of Electrical and Computer Engineering at Democritus University of Thrace. He is member of IEEE and the Technical Chamber of Greece. His research interests are in electrical machines, power production from small hydro, wind energy conversion and photovoltaics, power systems and electrical installations.

Theodore L. Kottas (1978) received his Diploma in Engineering degree and M.Sc. from the Electrical and Computer Engineering Department of the Democritus University of Thrace, Greece, in 2003 and 2005, respectively. He is currently a Ph.D. student at the Automatic Control Systems Lab of the Department of Electrical and Computer Engineering at Democritus University of Thrace. He is a student member of IEEE and member of the Technical Chamber of Greece. His research interests are in intelligent modelling and control techniques with applications in power production and conversion.

Dr. Yiannis S. Boutalis received his Diploma in Electrical Engineering in 1983 from the Democritus University of Thrace (DUTH), Greece and the Ph.D. degree in Electrical and Computer Engineering 1988 from the Computer Science Division of National Technical University of Athens, Greece. Since 1996, he serves as a faculty member, at the Department of Electrical and Computer Engineering, DUTH, Greece, where he is currently an Associate Professor. He served as an assistant visiting professor at University of Thessaly, Greece, and as a visiting professor in Air Defence Academy of General Staff of airforces of Greece. He also served as a researcher in the Institute of Language and Speech Processing (ILSP), Greece, and as a managing director of the R&D SME Ideatech SA, Greece, specializing in pattern recognition and signal processing applications. His current research interests are focused in the development of Computational Intelligence techniques with applications in Control, Pattern Recognition, Signal and Image Processing Problems.