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Intelligent methods of maximum power point tracking in photovoltaic systems

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***Abstract*— Renewable energy resources have enormous potential and can meet the present world energy demand, Photovoltaic system PV is one of green source of energy which continues to gain wide acceptance as one of the energy solutions in the future. The aim of the present research is the comparative study of variety controller of maximum power point tracking (MPPT) in photovoltaic system under variable meteorological conditions. The first controller refers to traditional approach based on the incremental conductance (INC), the second and third one, refers to new approach, based respectively on fuzzy logic (FC) and artificial neural network (ANN). The performances of these adopted controllers are examined and compared through a series of simulation which shown the good tracking and rapid response to change in different meteorological conditions of intelligent controllers compare with the conventional one.**

***Keywords*— Photovoltaic; INC; neural network; fuzzy logic**

I. INTRODUCTION

The importance of solar PV was emerging as replaceable energy resources for humans [1]. Indeed, PV systems are one of green energy sources, which are developing rapidly and have played a very important role in the electronic power field.

But the PV system present problem of low energy conversion efficiency and the output power depend on the atmospheric conditions (solar irradiation and temperature), so a controller named maximum power point tracker MPPT is needed to extract the maximum power at the terminals of PVG.

The incremental conductance is one of the most commonly used MPPT methods, but this method has presents limitations in their efficiency to track maximum power point as fast as possible to reduce oscillations in output power systems [2].

In this paper, we propose to study the modeling of a photovoltaic system and to find a method for optimizing the operation of the PV generator using INC controller, intelligent fuzzy logic and neural network controller.

II. PHOTOVOLTAIC POWER GENERATION

The solar cell is the basic unit of a photovoltaic module, which the large majority existing in the market is manufactured in silicon. It is the element in charge of transforming the sun rays or photons directly into electric power [3].

Fig. 1 illustrates the output characteristics P-V of PVG for different irradiation, as we can see there is maximum power point MPP, so in order to extract at each moment the maximum power at the terminals of PVG, insertion of maximum power point tracker (MPPT) is necessary between the photovoltaic module and load.

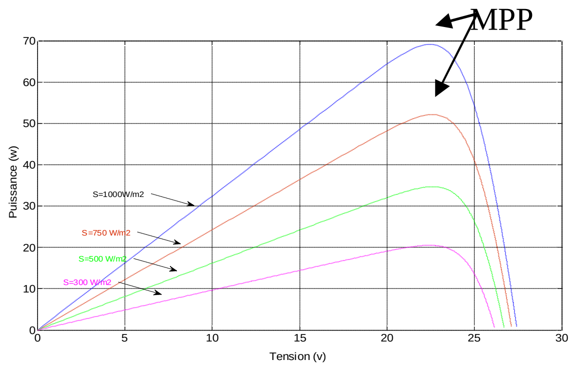

Fig. 1 Power curve under standard condition

In the following, the effectiveness of three proposed controllers are thoroughly investigated and compared via numerical simulation.

III. INCREMENTAL CONDUCTANCE CONTROLLER

The incremental conductance (INC) algorithm is derived by differentiating the PV module power equation with respect to voltage and setting the result equal to zero [4]–[5].

This is shown in follow Equations:

$$P=V*I \tag{1}$$

Differentiating equation (1) with respect to dV:

$$\frac{1}{V}\frac{dP}{dV}=\frac{I}{V}+\frac{dI}{dV}=G+\Delta G \tag{2}$$

From equation (2), the basic equations of this method are as follows:

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$$\frac{□□}{□□} □ 0 \quad □□ \quad \frac{□}{□} □ □ \frac{□□}{□□} \qquad □3□$$

$$\frac{□□}{□□} □ 0 \quad □□ \quad \frac{□}{□} □ □ \frac{□□}{□□} \qquad □4□$$

$$\frac{□□}{□□} □ 0 \quad □□ \quad \frac{□}{□} □ □ \frac{□□}{□□} \qquad □5□$$

Fig. 2 shows the flow chart of the Incremental Conductance (INC) method.

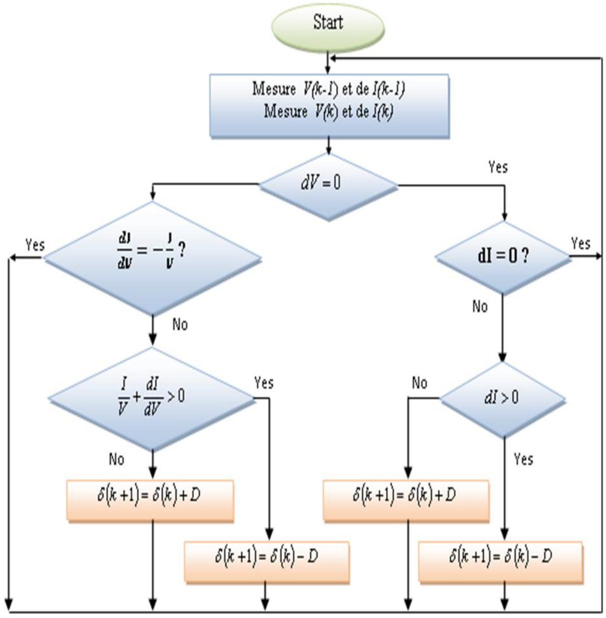

Fig. 2 Chart of the algorithm Incremental Conductance (INC)

Results of simulation for different tests obtained with the INC algorithm are presented and compared to those obtained with the neural network and fuzzy logic controller in section 6.

IV. Fuzzy logic

Fuzzy logic control generally consists of three stages (Show Fig. 3) which are briefly presented below:

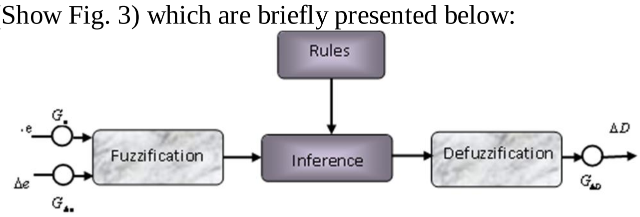

Fig. 3 Basic structure of fuzzy logic control

Fuzzification interface: the system convert the input variable to linguistic variable and define the membership function for each input variable.

Our MPPT controller has two inputs and one output. The two FLC input variables are the error E and the change of error φE (Equation 6) where:□ and □□ are the error and change in error, n is the sampling time, P(n) is the instantaneous power of the PVG, and V(n) is the corresponding instantaneous voltage.

$$\begin{cases} E(n) = \dfrac{P(n)-P(n-1)}{V(n)-V(n-1)} \\ \Delta E(n) = E(n) - E(n-1) \end{cases} \qquad (6)$$

The input of MPPT controller $E(n)$ shows if the load operation point at the instant n is located on the left or on the right of the maximum power point on the PV characteristic, while the input $\Delta E(n)$ expresses the moving direction of this point. The output variable is the duty cycle D, which is transmitted to the boost DC/DC converter to drive the load.

Inference and rule base: The mechanism of inference allows obtaining, by using the membership of every linguistic variable and the rule base the membership function of under fuzzy set solution of the command.

The defuzzification: the fuzzy logic controller output which is the duty cycle D is converted from a linguistic variable to a numerical variable.

The MPPT using the Mamdani FLC approach, which uses the minï max operation fuzzy combination law, is designed in a manner that the control task try to continuously move the operation point of the solar array as close as possible to the maximum power point (MPP) [8], and the defuzzification uses the center of gravity to compute the output of this FLC.

These two variables and the control duty cycle D used in our application are illustrated in Fig. 4

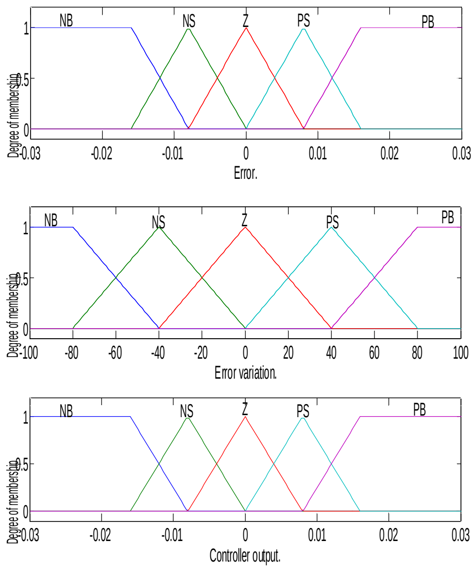

Fig. 4 Membership function of FLC

The results of simulation for different tests obtained with the FLC controller are presented and compared to those obtained with the others controllers are presented in section 6.

V. Neural network

The artificial neural network (ANN) is considered as an assembly of elements of identical structure called cells (or neurons) interconnected like cells of the vertebrate nervous system. Each point of connection (called the coefficient or weight) between two cells acts as a synapse, the main element of interaction between neurons. These connections or synaptic weights have a role in the parallel operation and adaptive neural networks where the notion of connectionist [3].

Artificial neural networks are computational systems that their architecture and functionality is inherited from the recently acquired knowledge of the biological computational units namely the brains neurons. Artificial Neural networks have already been used in meteorology in modeling several real-life problems, such in revealing connections between data i.e. the classification of synoptic weather types from height patterns [6]ï [7].

Fig. 5 Show us the schematic representation of a simple artificial network model. The artificial neuron has as an input value that are multiplied by a weight which is the “value” that the network gives at that point of the network. Then, it sums all the products and feeds the result to the activation function. The activation function alters the signal accordingly and passes the signal to the next neuron [8].

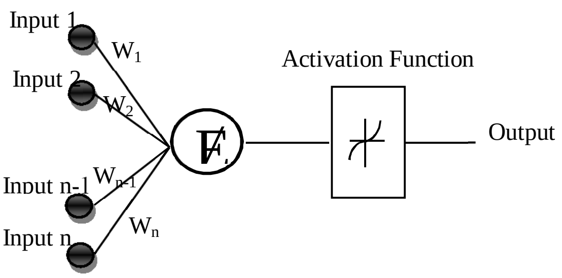

Fig. 5 Artificial neurons network

Learning in ANNs involves adjusting the weights of interconnections to achieve the desired input/output relation of the network; the output of neuron is described by mathematical formulation.

$$S = f\left(\sum_{j=1}^{i} W_i . E_i\right) \tag{7}$$

Our objective is to replace the INC controller by the neural network which is selected as a static, multilayer network. As shown in Fig. 6, it consists of three layers as follows:

An input layer with two neurons, two hidden layers: the first with 5 neurons and the second with 8 neurons, an output layer with one neuron.

In addition, the activation functions are adopted for the hyperbolic sigmoid neurons entered, and those of hidden layers, whereas that corresponding to the output neuron is chosen linear.

The entries of a neural network are considered to be the temperature T and the irradiations S, while the output of the neural network corresponds to the ratio cyclic D.

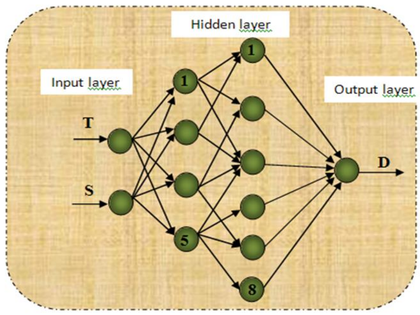

Fig. 6 The proposed neural network architecture

The number of neurons in the hidden layer has been optimized empirically during the learning phase. Indeed, the tests have shown that the most stable structure is composed of five neurons in first hidden layer and eight neurons for the second hidden layer. It is also noteworthy that the choice of the function activation of the hidden layer for which we opted, has been not chosen arbitrarily, but was implemented after several tests.

VI. Simulations & results

After conception, the three controllers are employed in different simulated control tasks of precise, robust and stable maximum power point.

The first test consists to compare the performance of this controller in standard condition, solar irradiation =1000w/m² and temperature of 25°C. Fig. 7 shows the result of the tracked power by different controllers.

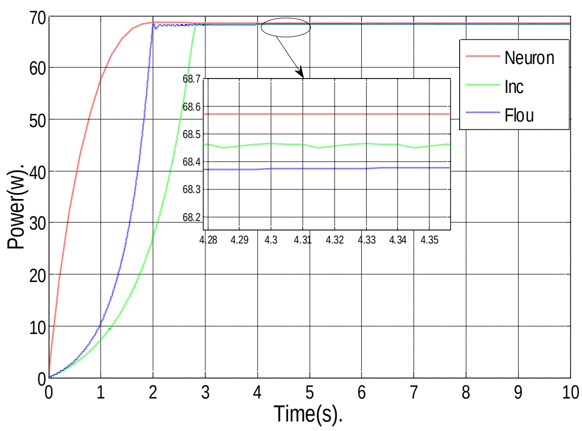

Fig. 7 Output power of PV systems in standard conditions

As can be seen, the ANN is more fast then the FLC and INC tracker, moreover the FLC based controller presents oscillations before achieve the MPP.

The next simulation is under the rapid variation of solar irradiation (from 1000w/m² to 900w/m² through 920w/m² in 2s); the results are shown in Fig. 8.

After that, the three controllers are also tested for rapid variation of temperature (increasing the temperature of 25 °C to 35°C in 0.1 s and decrease from 35°C to 25°C in 1s), (see Fig. 9.

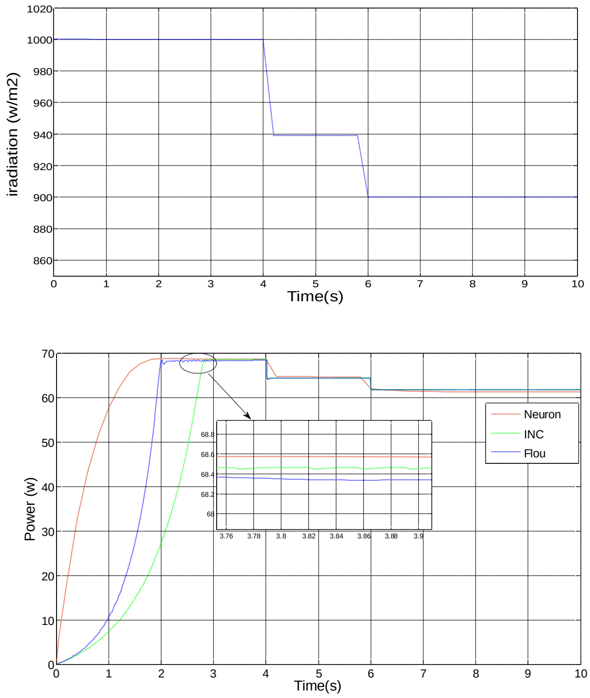

Fig. 8 Output power of PV for different irradiation

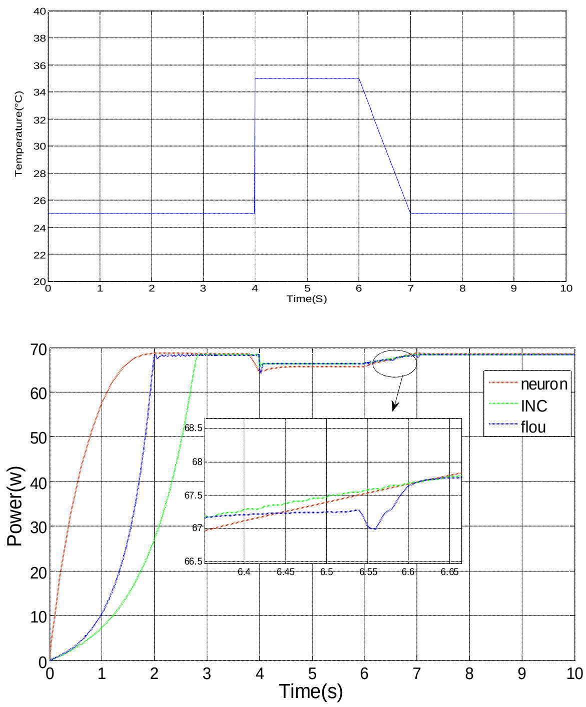

Fig. 9 Output power of PV for different temperature

As it is clearly shown, the ANN controller presents no overshoot and the maximum power point is well monitored by this controller in different condition unlike to the INC and FLC who present fluctuations when solar irradiation and temperature change.

The last simulation is under variation of following conditions such as: irradiation from 1000w/m² to 920w/m² and change back from 920w/m² to 1000w/m² in 0.1s, in addition of temperature increasing from 25 °C to 35°C in 2s.

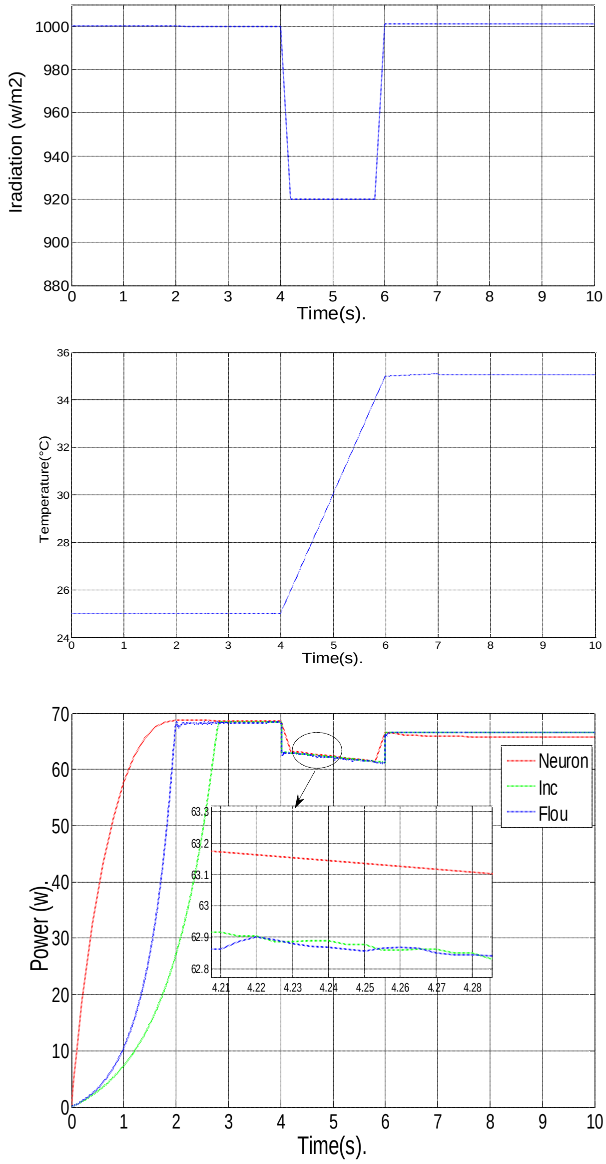

Fig. 10 PV systems response under varying condition of temperature and irradiation

As can be observed, ANN controller behaves exactly as expected for different variations considered, nevertheless the FLC and INC controller present oscillations to track MPP.

VII. Conclusion

In this paper we have investigated three types of controllers; conventional controller based INC and artificial intelligent controller based on Neural network and fuzzy logic, in order to track the MPP of photovoltaic system under different temperature and irradiation conditions.

According to the obtained results it is clear that the first controller INC is very simple to implement and can be carried out easily but presents oscillations around MPP.

The two intelligent controllers present a good performance as a fast responses for ANN, no overshoot in neural network controller and some fluctuations in FLC one.

Ongoing research and in order to get the fast responses and robust tracker to climatic change, a combination of the two controllers will be developed.

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