Development of Artificial Neural Network based MPPT for Photovoltaic System during Shading Condition

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Abstract. This paper presents Feedforward Neural network (FFNN) and Elman network controllers to control the maximum power point tracking (MPPT) of photovoltaic (PV). MPPT is a method used to extract the maximum available power from photovoltaic module by designs them to operate efficiently. Thus, cell temperatures and solar irradiances are two critical variable factors to determine PV output powers. The performances of the controller is analyzed in four conditions which are i) constant irradiation and temperature, ii) constant irradiation and variable temperature, iii) constant temperature and variable irradiation and iv) variable temperature and irradiation. The proposed systems are simulated by using MATLAB-SIMULINK. Based on the results, FFNN controller has shown the better performance compare to the Elman network controller during partial shading conditions.

Introduction

Since 1970's PV power generation systems have intensively investigated as an environment-friendly technology because of their advantages of infinite energy resources and no emission of carbon dioxide (CO_2) [1]. In order to increase the efficiency of PV module, lots of tracking control have been introduced, designed and applied, to help PV module operates to achieve maximum power point (MPP). The most common techniques that have been used were such as Perturb and Observe, constant voltage, neural network and fuzzy logic [2-4].

The main purpose of this paper is to discuss the development of FFNN and Elman network based MPPT control of PV system. This is due to the PV ineffectively producing the MPPT in certain time especially during shading condition. Since, partial shading has been identified as a main cause for reducing energy of many PV systems. To achieve the objective of this project, MATLAB-SIMULINK software is used to analysis the MPPT for PV system from the simulation result of FFNN and Elman networks.

There have many reason lead to the PV array had been shaded. One of an unavoidable issue is cloudy day that lead to non-uniform irradiance, that cause more complicated current-voltage (*I*–*V*) and power-voltage (*P*–*V*) with multiples local MPP. Hence, the controller is difficult to generate the optimum MPP.

Consequently, this project is to analyze and compares the simulation result of FFNN and Elman networks in four conditions during constant irradiation and temperature, constant irradiation and variable temperature, constant temperature and variable irradiation, and variable temperature and irradiation.

PV Modules Modeling

The main source of power for the photovoltaic system is based on solar panel. The equivalent electrical circuit model are the main element of the panel is formed by a current source that depends on the solar radiation in W/m2, temperature in Celsius degrees (*T*), a shunt diode whose intensity of inverse saturation in series depends on the temperature and a resistance (RS), which represents the effect of the internal resistance of each solar cell.

As mention, MATLAB-SIMULINK is used to designing a program by taking into account the number of solar cells which has in PV panel. The main equation shown in Eq. (1) is to calculate the photocurrent, I_{ph} of PV system at the suitable working temperature, T_{ak}.

$$I_{ph} = I_{ph_{T1}} \times (1 + a) \times (T_{ak} - T_1) \tag{1}$$

While, the first working temperature, T_1 can be calculated by substitute the Eq. (2) into Eq. (1)

$$Iph_{T1} = Isc_{T1} \times Suns \tag{2}$$

and, a is the ratio of short circuit current at T_1, Isc_{T1} and the short circuit current at T_2, Isc_{T2}, that can be calculated using Eq. (3).

$$a = \frac{Isc_{T2} - Isc_{T1}}{Isc_{T1} \times (T2 - T1)} \tag{3}$$

The saturation current is shown in Eq. (4), where $b = Vg \times q/(A \times k)$; Vg= 1.12 eV is diode voltage for crystalline Silicon <1.75 for amorphous silicon, with the reference temperature of T_{Ref}.

$$I_r = I_{rT1}\left(\frac{Tak}{T_{\text{Ref1}}}\right)^{\frac{3}{A}} \times e^{\left[-b\left(\frac{1}{T_{\text{Ref}}} - \frac{1}{T_C}\right)\right]} \tag{4}$$

The I_{ph} is directly proportional to solar radiation IRA which taking into account a constant of proportionality, according to the Eq. (2). The terms of reference are solar radiation (IRA=1, Sun=1000 W/m2), atmospheric mass (AM=1.5) and temperature (T = 25 ˚C).

The relationship between the photocurrent and the temperature is linear, according to the Eq. (1) and follows from the variation of photocurrent with temperature variation. When the panel is short circuited and illuminated, the photocurrent flows in it's entirely by the diode. The value of reverse saturation current, I_r to 25 °C was calculated from the short circuit current and open circuit voltage at this temperature as shown in Eq. (3) [5]. Finally, the value of diode ideality factor is referring to the data appears in the specifications sheets and is provided by the manufacturer.

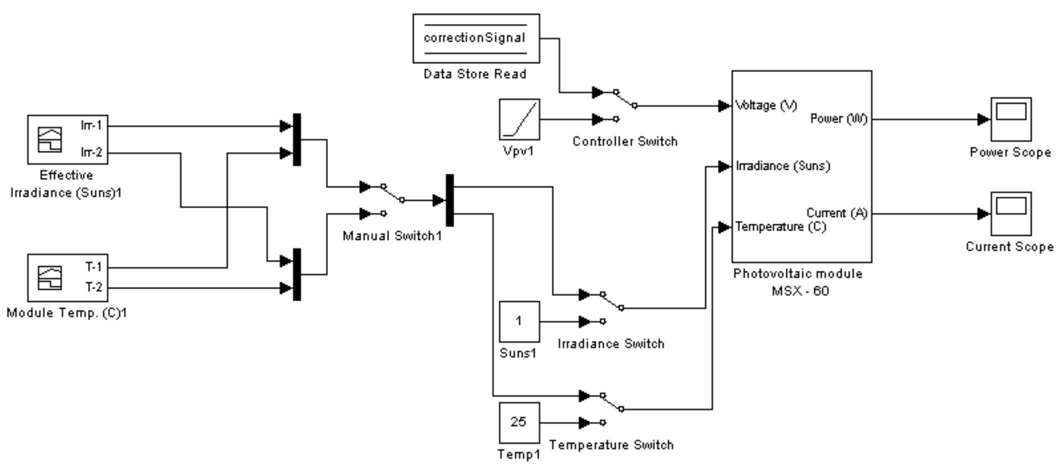

Figure 1: Masked block diagram of the modeled solar MSX -60 PV

In this project, the Solarex MSX -60 photovoltaic module is used. The Typical Electrical Characteristics of MSX-60 PV modules is available as in [6].By knowing all the important required equations of the generalized PV model, it subsystem can be developed. The block diagram of the solar MSX-60 PV modules is shown in Fig. 1. The inputs to the solar PV panel are cell temperature, solar irradiation and voltage.

While, the MPPT algorithms are designed to dynamically extract the maximum power from the PV panels. Usually, the condition $\partial p/\partial v = 0$ is adopted to locate this operating point, since PV panels show a unique global MPP. The MPPT algorithms are based on the determination of the slope of the PV panel's output power versus voltage, i.e., the power derivative $\partial p/\partial v$. The typical characteristics of the power generated by a panel for varying levels of sunlight are outlined in Fig. 2. For different level of radiation, there is a point at which the panel gives the MPP [7].

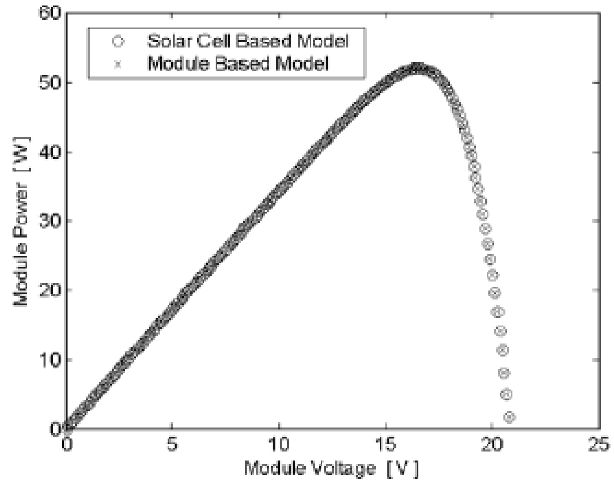

Figure 2: Power–voltage (P–V) characteristics without mismatching (Sun=1000W/m^2, T=35°C) [7]

Controllers

Neural network techniques have been used to solve complicated practical problems in various areas and are becoming more popular, thus it becoming practical as alternate approaches to conventional techniques [8].

FFNN. Three layers (sometimes called two layers) and FFNN are commonly encountered models in different literatures. Computation nodes are arranged in layers and information feeds forward from layer to layer via weighted connections as illustrated in Fig. 3. Circles represents computation nodes (transfer functions), and lines represents weighted connections. The bias shareholding nodes are represented by squares.

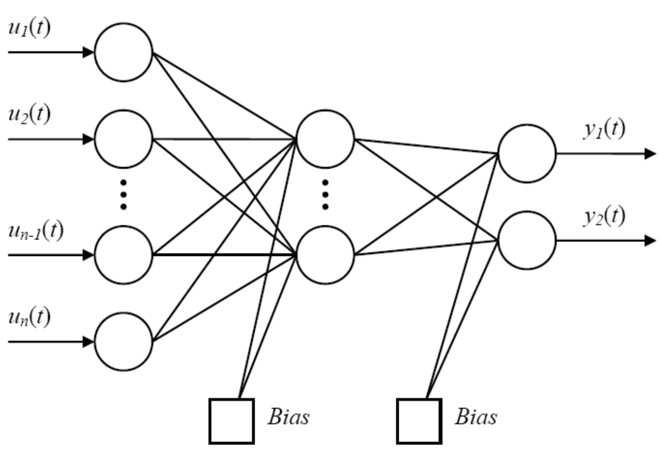

Figure 3: Block Diagram of FFNN

Typical FFNN can be expressed as Eq. (5),

$$y_i = \varphi_0\left[C\varphi_h\left(Bu_i + b_h\right) + b_0\right] \tag{5}$$

where y_i is the output vector corresponding to an input vector u_i, C is the connection matrix (matrix of weights) represented by arcs (the lines between two nodes) from the hidden layer to the output layer, B is the connection matrix from the input layer to the hidden layer, and b_h and b_o are the bias vectors for the hidden and output layers, respectively. $\varphi_h(.)$ and $\varphi_0(.)$ are the vector valued functions corresponding to the activation (transfer) functions of the nodes in the hidden and output layers, respectively. Thus, FFNN models have the general structured as Eq. (6)

$$y_i = f(u) \tag{6}$$

where $f(.)$ is a nonlinear mapping. Hence, a FFNN is structurally similar to nonlinear regression models. The (6) represents a steady state process.

Elman Network. Fig. 4 shows the block diagram of Elman Network. The Elman network is a three layer (sometimes called a two-layer) network with a feedback from output of a hidden layer to the input of a hidden layer.

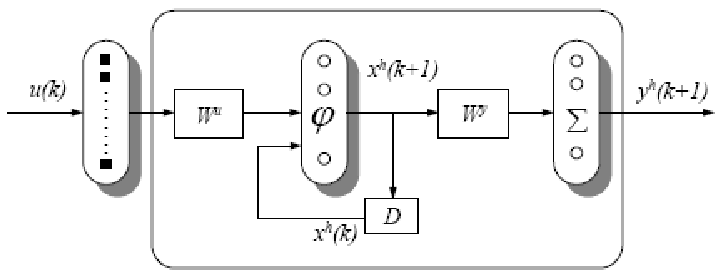

Figure 4: Block Diagram of Elman network

To understand the feature offered by Elman network, consider a multivariable plant with m inputs and q outputs, described by a general nonlinear input-output discrete time state space model [9].

$$x(k + 1) = f\,\{x(k), u(k)\} \tag{7}$$

$$y(k) = g\,\{x(k)\} \tag{8}$$

where $f : \Re^{n+p} \rightarrow \Re^n$ and $g : \Re^n \rightarrow \Re^q$ are non-linear functions; $u(k) =\in \Re^m$, $y(k) \in \Re^q$ and $x(k) \in \Re^n$ are the input vector, the output vector and the state vector, at a discrete time k, respectively. In addition to the input and the output units, the Elman network has a hidden unit, $x^h(k) \in R^n \cdot W^u \in \Re^{nxp}$ and $W^y \in \Re^{qxn}$ are the interconnection matrices for the input-hidden layer and hidden-output layer.

Theoretically, an Elman network with n hidden units is able to represent an n^{th} order dynamic system. The dynamics of the Elman network are described by different equations as in Eq. (9)-(11).

$$s(k + 1) = x^h(k) + W^u u(k) \tag{9}$$

$$x^h(k + 1) = \varphi\,\{s\,(k + 1)\} \tag{10}$$

$$y^h(k + 1) = W^y x^h(k + 1) \tag{11}$$

where $s(k) \in \Re^n$ is an intermediate variable and $\varphi\,(\cdot)$ is an activation (transfer) function.

Note that the Elman network differs from conventional two-layer network because its first layer has a recurrent connection. The delay in this connection stores values from previous time step, which can be used in the current time step. Because the network can store information for future references, it can learn temporal patterns as well as spatial patterns. The Elman network can be trained to respond to and to generate both kinds of patterns.

In the configuration of neural network model, for FFNN and Elman networks, a logsig (log-sigmoid) transfer function is used in its hidden layer and purelin (linear) transfer function in its output layer. With this combination, the network can give approximations to any function.

Results and Analysis

The performance of the developed controller, namely FFNN and Elman network controller are analyzed in four conditions:

1) Constant irradiation and temperature
2) Constant irradiation and variable temperature
3) Constant temperature and variable irradiation
4) Variable temperature and variable irradiation

The metrics that are used to measure the performance are the maximum power, voltage and current achieved by the solar panel, and the time.

Comparison of Temperature and Irradiation Effects on FFNN and Elman network Controllers. From Table 1, it can be seen that the FFNN controller results in the solar panel reaching the MPP point faster as compared with the Elman network. With a comparable of maximum power value, the FFNN controller is able to reach MPP within 0.9 seconds for a maximum power of 69.24 W. Tmax is represent the total simulation time for controller to respond to input variable. From observation it shows for input parameters during variable irradiance and constant temperature were gave very low power for Pmax of Elman network. This phenomenon is due to slow computation of Elman network when handle with huge input variable. The same reason happened as shown in Table 2 for switch 2 of Elman network.

Table 1: Comparison of Temperature and Irradiation Effects on FFNN and Elman Network Controller

Parameters	FFNN			Elman Network		
	Constant Irr, Const Temp	Constant Irr, Variable Temp	Variable Irr, Const Temp	Constant Irr, Const Temp	Constant Irr, Variable Temp	Variable Irr, Const Temp
Pmax	64.44 W	69.24 W	63.11 W	64.44 W	62.01 W	7.695 W
Vmax	18.1 V	19.8 V	18.12 V	18.06 V	16.57 V	17.6 V
Imax	3.56 A	3.497 A	3.483 A	3.568 A	3.741 A	0.437 A
Tmax	0.8 s	0.9 s	0.8 s	0.83 s	0.96 s	0.8 s

Comparison of FFNN and Elman Network Controller (Variable temperature and variable irradiation). The results from Table 2 have shown the FFNN and Elman network controller in two different stages. Which, the inputs for these two controllers are analyzed by the two categories variance irradiance and temperature, which are switch 1 and switch 2, respectively. Meanwhile, switch 1 is represented normal irradiance which is sunny day. On the other hand, switch 2 is represented partially shaded conditions. For the case where both of controllers are turned to switch 1, the result for the maximum power of the FFNN controller is slightly higher than the Elman network controller. The FFNN controller is able to reach the MPP within 0.81 seconds for a maximum power of 21.36 W. While, when the switch is turned to switch 2, maximum power of FFNN controller still remains higher than the Elman network.

Table 2: Comparison of Two Different Temperature and Irradiation Effects on FFNN and Elman Controller

Parameters	**FFNN Controller**		**Elman Controller**	
	Switch 1	**Switch 2**	**Switch 1**	**Switch 2**
Pmax	21.36 W	51.04 W	6.103 W	6.099 W
Vmax	19.2 V	18.36 V	17.44 V	16.57 V
Imax	1.113 A	2.78 A	0.35 A	0.368 A
Time	0.81 s	0.8 s	1.96 s	0.05 s

Conclusion

This paper has presented the modeling of PV module and the development of the MPPT techniques. The PV controller's performances are analyzed in four conditions which are constant irradiation and temperature, constant irradiation and variable temperature, constant temperature and variable irradiation and variable temperature and variable irradiation. The proposed system is simulated by using MATLAB-SIMULINK. Based on the simulation result, the project is successfully achieving the objective.

From the simulation result, FFNN controller has shown the better performance compare to the Elman network controller during the sunny day and partially shaded conditions. Which, the FFNN controller has the greater maximum power compared to Elman network controller. The maximum power of sunny day and partial shaded condition for FFNN controller are 21.36 W and 51.04 W respectively, whereas, for the Elman network controller are 6.103 W and 6.099 W respectively. According the results again has proof the FFNN controller is the optimum controller. For real application the proposed method can be applied on FPGA board.

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