Contents lists available at Science-Gate

International Journal of Advanced and Applied Sciences

Journal homepage: http://www.science-gate.com/IJAAS.html

ANFIS-based PI controller for maximum power point tracking in PV systems

Hisham Hussein [1,*], Ali Aloui [1], Badr AlShammari [2]

[1]Department of Electronics Engineering, Community College, Ha'il University, Hai'l, Saudi Arabia
[2]College of Engineering, Ha'il University, Hai'l, Saudi Arabia

ARTICLE INFO

Article history:
Received 15 September 2017
Received in revised form
12 December 2017
Accepted 18 December 2017

Keywords:
Adaptive neuro-fuzzy inference system
Maximum power point
Fuzzy logic
Neural networks

ABSTRACT

This paper presents a maximum power point tracking (MPPT) control system which is designed to increase the energy generation efficiency of Photovoltaic (PV) arrays. Usually Maximum power point tracking control system uses dc-to-dc converters to compensate for the output voltage of the PV array in order to keep the voltage at the value, which maximizes the output power. The purpose of the work is to develop an adaptive neuro-fuzzy inference system (ANFIS)-based proportional integral controller. The operating temperature and level of irradiance constitute inputs for the ANFIS controller, allowing it to determine the maximum available power that the PV array possesses. The error between the reference power from the ANFIS controller and the measured voltage and current of the PV array enables the proportional integral controller to generate the duty cycle. It is shown that ANFIS-based PI controller gives better performance criteria, unlike conventional techniques which usually give associations at steady state operating conditions. Eventually, the proposed MPPT control system based on ANFIS could provide better results than conventional techniques in terms of performance, accuracy and stability.

1. Introduction

The use of fossil fuels to generate electric power is highly damaging to the environment. Therefore, renewable energy sources, such as solar energy, should be used instead as they are environmentally friendly. Industrial, governmental and private sectors all benefit from solar energy and related technology. However, for solar power to replace traditional energy resources, its cost per Kilowatt-hour must be demonstrated to be more advantageous (Govinda et al., 2011; Ansari et al., 2013).

There are various factors that influence the efficiency of photovoltaic (PV) arrays, including the temperature at which these arrays operate the ambient temperature, and the level of irradiance.

The ability of the PV arrays to produce power is not always the same, but oscillates according to changes in these influential factors, which display a great degree of dynamism (Zhou et al., 2007). Different mathematical models, proposed in the literature. Villalva et al. (2009), show the performance of the PV array against irradiance intensity and PV array temperatures.

The extraction of the maximum power point (MPP) from the PV array is the overall goal of the present study. To this end, there is a range of available methods, including the incremental conductance (INC) method, the perturb and observation (PandQ) method, neural networks (NN), fuzzy logic (FL), as well as other artificial intelligence (AI) methods (Liu et al., 2004; Wu et al., 2009; Azab, 2009; Kumari and Babu, 2011).

Among these methods, the one most widely applied due to its uncomplicated nature is the PandO method (Atallah et al., 2014). However, it presents certain limitations, such as the fact that it causes fluctuations in the operating mode around its MPP, because it is insufficiently accurate at steady-state operating conditions. Furthermore, MPP tracking will be unsuccessful if the irradiance intensity is not constant. Under such circumstances, the tracking can be made more accurate in varying environmental conditions, including abrupt changes, with the INC method (Lokanadham and Bhaskar, 2012; Mirbagheri et al., 2013). On the downside, the INC method makes the overall system more expensive because it requires extensive computational capacity.

* Corresponding Author.
Email Address: h.hussein@uoh.ed.sa (H. Hussein)
https://doi.org/10.21833/ijaas.2018.02.015

As argued by one study, system stability could not be ensured by the methods discussed above because they would cause fluctuations around MPP (Chao and Li, 2010). By contrast to standard methods, greater accuracy of systems, particularly non-linear systems, could be ensured with AI methods. The MPP has been frequently tracked with neural networks (NN) and fuzzy logic (FL) methods (Yousef, 1999; Chaouachi et al., 2010).

The adaptive neuro-fuzzy inference system (ANFIS) integrates the strengths of NN and FL methods and therefore is the most suitable for the suggested purposes of this study. The operating temperature and irradiance intensity constitute the inputs of the well-trained MPP ANFIS controller to derive maximum power from the PV array.

Furthermore, the set point and the crisp output of the proportional-integral (PI) controller are respectively represented by the output power generated by the ANFIS controller and the duty cycle of the pulse width modulation to switch the DC-DC converter. The PI controller generates the duty cycle based on the error between the reference power from the ANFIS controller and the measured PV array voltage and current. Fig. 1 shows the block diagram of the maximum power point tracking system (MPPT).

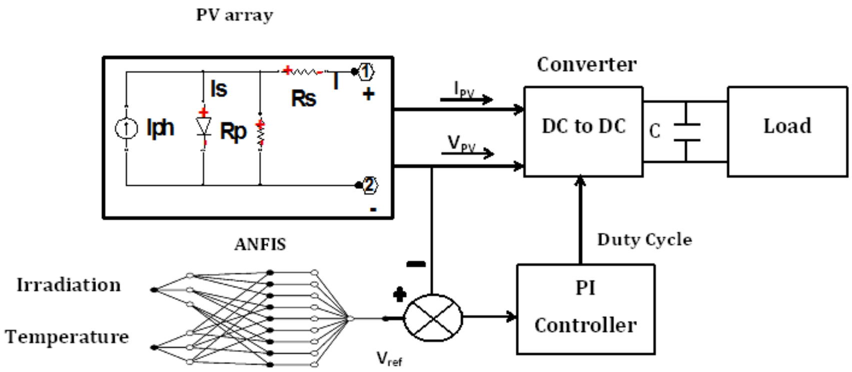

Fig. 1: The block diagram with MPPT control system

It is worth mentioning that an intensive work on ANFIS-based PI controller for MPPT control system is addressed in the literature (Singh and Pandit, 2013; Takun et al., 2011; Alabedin et al., 2011; Li and Wang, 2009). However, to the best of my knowledge, no papers have been addressed to the issue of ANFIS -based PI controller for an MPPT system in Hail region of Saudi Arabia. The main contribution of this paper is that it employs various data related to the PV array, such as level of irradiance and operating temperature, which are collected from the solar monitoring station of Hail Technical Institute and prepared by King Abdullah City for Atomic and Renewable Energy (KACARE, 2016).

The main contribution of the PV array solar data acquired from Hail station is to apply coupled input-output training data sets (e.g. PV array operating temperature and irradiance intensity measured in degrees Celsius and W/m^2, respectively) to an adaptive neuro-Fuzzy algorithm for the sake of optimizing the fuzzy logic controller membership functions, which would lead to a better tracking MPP controller.

The second contribution is that it affords an analysis of the feasibility of PV solar technology implementation in Hail region, enhancing the awareness of other academics and researchers in the field.

To derive the necessary control signal, an adaptive neuro-fuzzy logic controller will be developed on the basis of the input-output training data. It will be demonstrated that, by comparison to conventional methods, accuracy and performance are both improved by an ANFIS-based PI MPPT control system.

In the next section we will describe the mathematical modelling and characteristics of the solar cell which was used to provide the basis for further analysis and simulation.

2. The solar cell-induced current

2.1. Description of the solar cell characteristics

In order to get a better understanding of the solar cell and the dynamic interactions between its parameters, we will describe its equivalent circuit model (Gow and Manning, 1999). More specifically, we will use Matlab, Simulink and Simscape toolboxes. Fig. 2 illustrates the ideal equivalent circuit model of a solar cell.

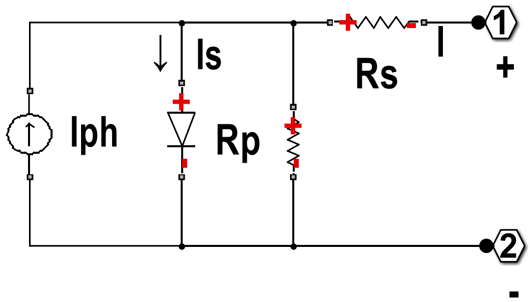

Fig. 2: The equivalent circuit of a solar cell

The equivalent circuit associated with a solar cell takes the form of a resistance (Rs) connected in series with a parallel combination of a current source, diode and parallel resistor (Rp).

To obtain the output current (I), the following formula is applied:

$$I = I_{ph} - I_s * \left(e^{\frac{V+I*R_S}{N*V_t}} - 1\right) - \frac{V+I*R_s}{R_p} \tag{1}$$

The solar-generated current is denoted by I_{ph} and calculated as:

$$I_{ph} = I_{ph0} \times \frac{I_r}{I_{r0}} \tag{2}$$

In the above, the irradiance that the cell is exposed to is denoted by I_r (W/m^2), the measured solar-generated current for the irradiance I_{r0}, and the diode's saturation current are respectively denoted by I_{ph0} and I_s, V_t is the thermal voltage (kT/q), where k, T and q respectively represent the Boltzmann constant, PV module temperature, and electron elementary charge, whilst N and V are the diode's quality factor and the voltage across the PV array electrical ports, respectively.

The temperature influences a number of parameters of the solar cell. The solar-generated current I_{ph} is correlated with the solar cell temperature T in the following way:

$$I_{ph}(t) = I_{ph} \times (1 + T_{IPH} \times (T - T_{meas})) \tag{3}$$

Where T_{IPH} is the temperature coefficient for I_{ph}, T_{meas} is the measured temperature value. The saturation current of the diode T_S is related with the solar cell temperature T as follows:

$$I_s(T) = I_s \times \left(\frac{T}{Tmeas}\right)^{(T_{XIS}/N)} * e^{(EG*(\frac{T}{T_{meas}}-1)/(N*V_t))} \tag{4}$$

Where T_{XIS} is the temperature coefficient associated with I_s.

In the next section, we will present the PV array model and its characteristics are presented in Matlab, Simulink and Simscape toolboxes.

2.2. The proposed model of the PV array

The Simscape model of the PV array is shown in Fig. 3. The PV array consists of a number of strings of modules connected in parallel and each string consists of a number of modules connected in series. We have used PV SunPower SPR305-WHT module type (Pierre et al., 2012) as a reference and its data specifications are shown in the following Table 1.

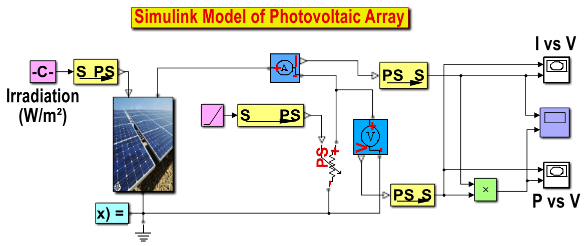

Fig. 3: The Simscape model of PV array

Table 1: Key specifications of SunPower SPR305-WHT PV module

Number	Parameter	Variable	Value
1	Maximum power	*PM*	305 kW
2	Voltage at maximum power	*Vm*	54.7 V
3	Current at maximum power	*Im*	5.58 A
4	Open circuit voltage	*Voc*	64.2 V
5	Short circuit current	*Isc*	5.96 A
6	Maximum power for the PV array	*PA*	100 kW
7	number of series-connected cells per module	*Nsc*	96
8	Number of series-connected modules per string	*Nsm*	5
9	Number of parallel strings	*Nps*	66

In the analysis of the simulations, it is revealed that with the increase in the solar irradiance intensity, the short circuit current and the open circuit voltage are also increasing (Pierre et al., 2012).

Fig. 4 shows I-V and P-V characteristics of one module at 25 degrees Celsius. Fig. 5 shows I-V and P-V characteristics of the array at 25 degrees Celsius. From the Figures, it is clearly shown that with the increase in irradiance, maximum output power from the module also increases.

In the next section, we will present the work methodology with the objective of developing effective MPPT control system.

3. Methodology

As shown from Figs. 4 and 5, it is apparent that the maximum power is available at one operating point and. this point is called maximum power point (Pierre et al., 2012). It greatly depends on solar irradiance intensity level and operating temperature. That is, the MPP varies with the change of these variables.

Maximum power point tracking controllers are used for tracking the maximum power operating point under rapidly changing irradiance and temperature conditions. Consequently a properly designed MPPT controller would track the maximum power operating point in order to increase the efficiency of the PV array. The next steps describe the development of MPPT control system for the sake of maximizing the power point tracking in PV systems.

3.1. MPPT using ANFIS

The proposed ANFIS PV MPPT Simscape model is shown in Fig. 6.

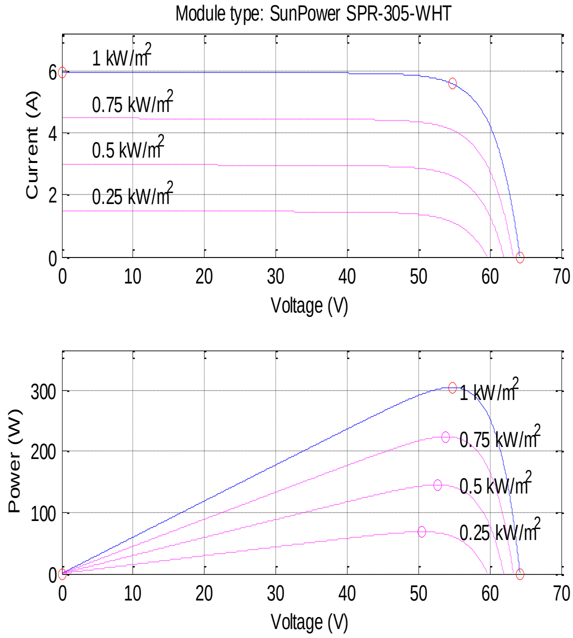

Fig. 4: I-V and P-V characteristics of one module at 25 degrees Celsius and variable irradiance level

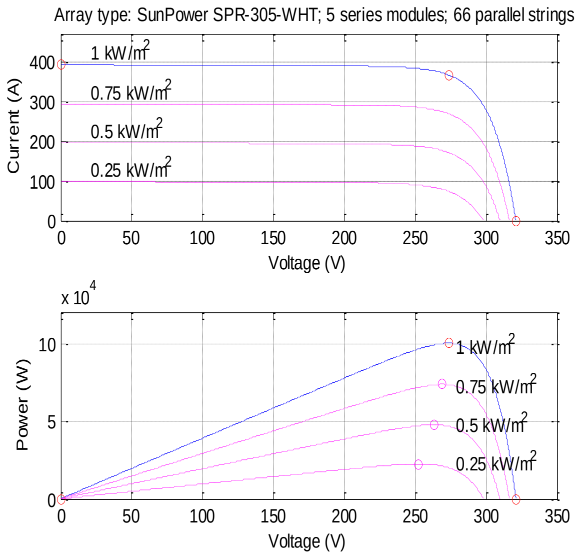

Fig. 5: I-V and P-V characteristics of the array at 25 degrees Celsius and variable irradiance level

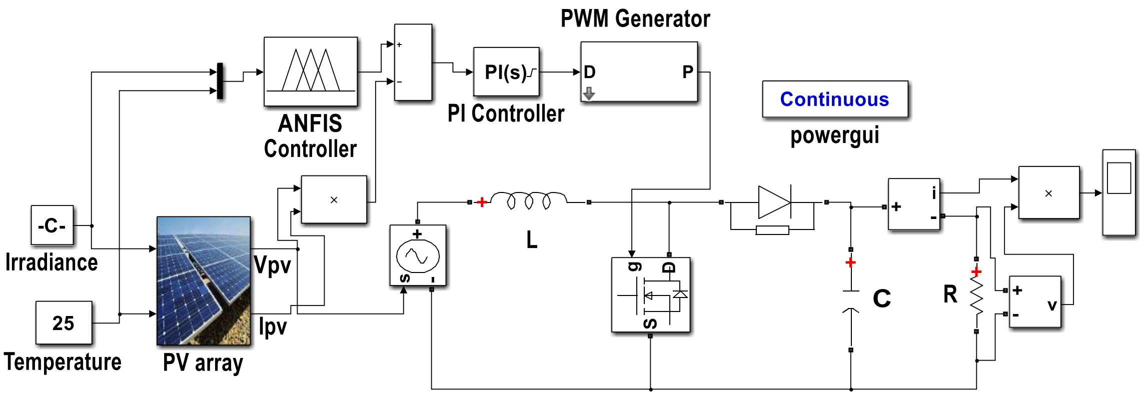

Fig. 6: The Simscape model of ANFIS PV MPPT control system

The ANFIS controller uses irradiance level and operating temperature of the PV array as input.

Therefore, the ANFIS controller provides the PI controller with the reference value of the existing maximum power at a particular temperature and irradiance intensity.

At the same temperature and irradiance level, the actual output power from the PV array is extracted and compared with the set point value from the ANFIS controller. Consequently, the error is given to a proportional integral (PI) controller which would then generate the control signal to the PWM generator.

The generated PWM signal would then control the duty cycle of the DC–DC converter, in order to adjust the operating point of the PV array voltage.

3.2. ANFIS training technique

In order to extract the input/output training data sets for the ANFIS controller, we have used the data obtained from KACARE in a step fashion way.

Thus, variation in a step of 5°C in the range 15-65°C has been applied to the operating temperature, while the irradiance intensity has been subjected to variation in a step of 50 W/m² within the range 100-1000 W/m².

Consequently, the maximum available power for each pair of training data is recorded. 60 training data sets and 300 epochs have been used to train the ANFIS controller. The hybrid optimization algorithm has been subsequently applied to adjust the membership function parameters of the fuzzy inference system (FIS) created by ANFIS.

This algorithm integrates least-square and back propagation techniques (Jang, 1993; Jang, 1991). The training error is reduced to approximately 8% and the training error plot is shown in Fig. 7.

The training data and ANFIS output are illustrated in Fig. 8.

The training error shows that the ANFIS output goes with the actual output of the PV array, even at 8%. The structure of ANFIS is a five layer network as shown in Fig. 9.

It has two inputs (irradiance level and operating temperature), one output and three membership functions for each input. The membership functions for each input, after training the ANFIS controller, are shown in Figs. 10 and 11.

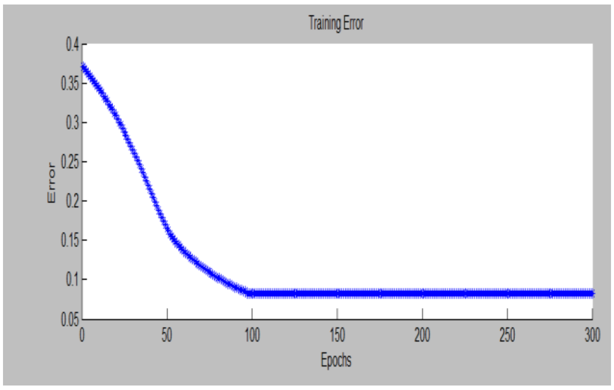

Fig. 7: The training error versus epochs for the ANFIS controller

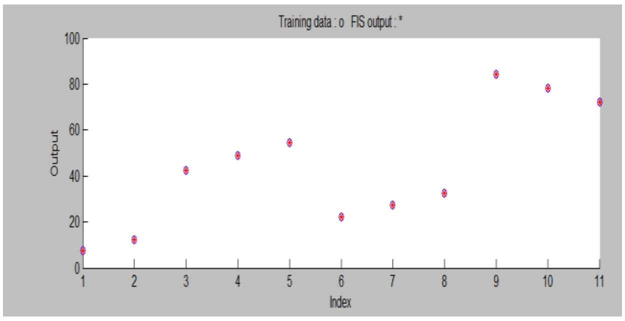

Fig. 8: Training data and ANFIS output

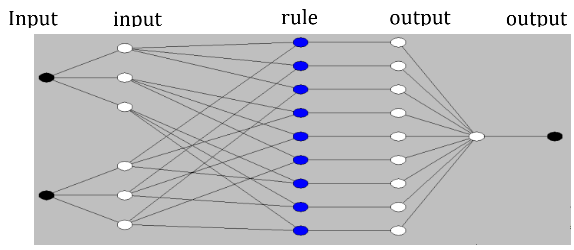

Fig. 9: ANFIS model structure

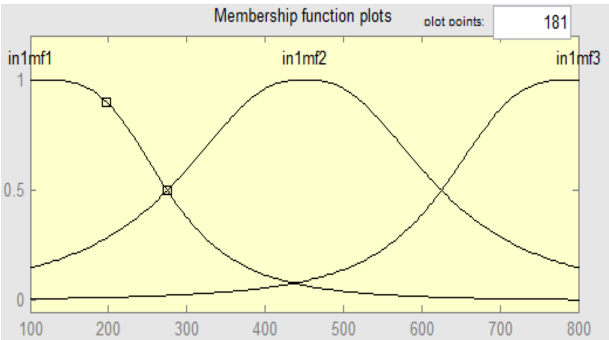

Fig. 10: Membership functions of ANFIS input (Irradiance) after learning

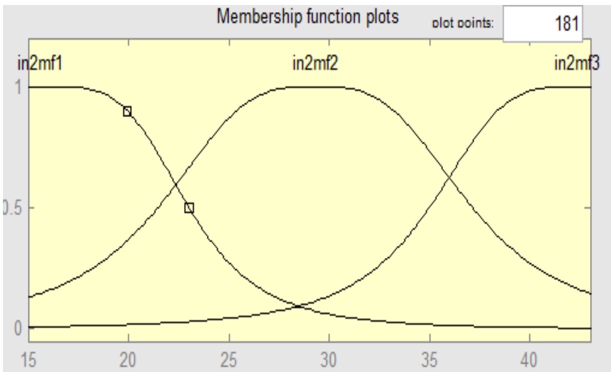

Fig. 11: Membership functions of ANFIS input (Temperature) after learning

As a result, nine fuzzy rules were developed from six input membership functions. In addition, these rules are developed according to the input and output mapping, in such away maximum output power for each value of the input temperature and irradiance level is received.

In the next section, we will demonstrate the simulation results for the developed MPPT control system that was described above.

4. Simulation results and discussions

In general, when a PV module is directly connected to a load, the operating point is seldom at the MPP.

There so MPP tracking control systems use dc-to-dc converter to compensate for the output voltage of the PV module in order to keep the voltage at the required value, which maximizes the output power of the PV module.

The Simscape control model was used to simulate the proposed ANFIS-based PI MPPT control system. The ANFIS controller varies the duty cycle of the boost converter in order to transfer the maximum available power to the load.

It was simulated to demonstrate the capabilities and performance of the ANFIS control scheme.

Fig. 12 demonstrates the effect of the ANFIS controller on the PV array power as transients vanished very quickly and the system reached the maximum output power (100kW) at irradiation level of 1000 W/m2 after a very small settling time.

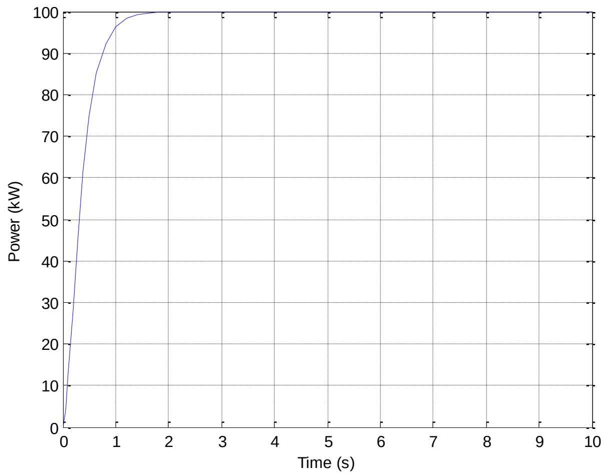

Fig. 12: The PV array power response with ANFIS controller

For the sake of comparison, we have simulated the same PV array system but without any controller. Fig. 13 shows the output power of PV module without MPPT control scheme at irradiance level of 1000 W/m2.

The simulation results clearly indicate that the presence of the ANFIS controller enhanced the PV output power by 20% at 1000 W/m^2 irradiance intensity.

The obtained results from the ANFIS-based PI MPPT control system show several benefits over the aforementioned conventional techniques. It gives better performance criteria in terms of shorter rise time and smaller overshoot than conventional techniques.

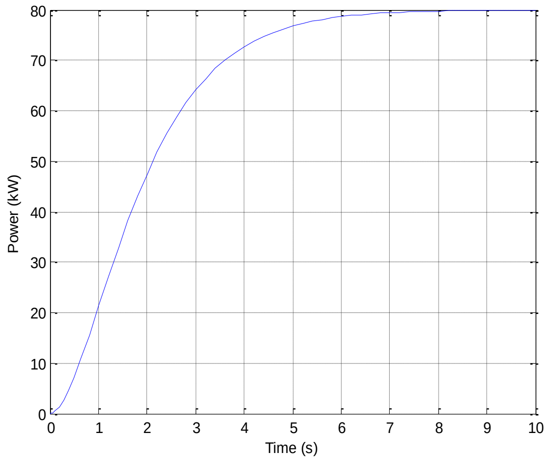

Fig. 13: The PV array power response without ANFIS controller

In addition, it handles the rapidly varying environmental conditions (like temperature and irradiance level) without producing oscillations at steady state mode.

5. Conclusion

In this paper, an adaptive neuro-fuzzy logic based proportional integral controller for maximum power point tracking control system has been proposed for a solar PV array.

The operation of the ANFIS-based PI MPPT controller has been investigated under varying climate conditions. From the simulations, it is clear that the ANFIS controller gave excellent results in terms of extracting the maximum power from the PV array with greater accuracy.

In addition, ANFIS-based PI controller gave better performance criteria in terms of shorter rise time and settling time unlike conventional techniques such as PandO technique.

Usually PandO technique does not give accurate MPP at steady state operating conditions and in order to avoid these associations, perturbation size should be reduced at the expense of significantly larger settling time and larger rise time.

So there always would be a trade-off between performance and stability. The MPP tracking could be more accurate in varying operating conditions with the incremental technique, but unfortunately makes the system more expensive.

Therefore, ANFIS based PI control technique could provide a better control than conventional techniques in terms of performance and accuracy.

Nevertheless, it is worth mentioning that ANFIS based PI control drawbacks are related to tuning difficulties of membership functions and scaling factors which can be resolved using different optimization algorithms without degrading its performance.

Acknowledgment

I would like to thank the Academic Research Deanship at Hail University for providing financial support under the research grant No. 0150440. I would like also to express my deepest appreciation to the reviewers for their helpful comments and suggestions.

References

Alabedin AZ, El-Saadany EF, and Salama MMA (2011). Maximum power point tracking for Photovoltaic systems using fuzzy logic and artificial neural networks. In the Power and Energy Society General Meeting, IEEE, Detroit, MI, USA: 1-9. https://doi.org/10.1109/PES.2011.6039690

Ansari MF, Kharb RK, Luthra S, Shimmi SL, and Chatterji S (2013). Analysis of barriers to implement solar power installations in India using interpretive structural modeling technique. Renewable and Sustainable Energy Reviews, 27:163-174.

Atallah AM, Abdelaziz AY, and Jumaah RS (2014). Implementation of perturb and observe MPPT of PV system with direct control method using buck and buck-boost converters. Emerging Trends in Electrical, Electronics and Instrumentation Engineering: An International Journal, 1(1): 31-44.

Azab MA (2009). New maximum power point tracking for photovoltaic systems. International Journal of Electrical and Electronics Engineering, 3(11):702-705.

Chao KH and Li CJ (2010). An intelligent maximum power point tracking method based on extension theory for PV systems. Expert Systems with Applications, 37(2): 1050-1055.

Chaouachi A, Kamel RM, and Nagasaka K (2010). A novel multi-model neuro-fuzzy-based MPPT for three-phase grid-connected photovoltaic system. Solar Energy, 84(12): 2219-2229.

Govinda RT, Kurdgelashvili L, and Patrick AN (2011). Review of solar energy: Markets. Economics and Policies. No. WPS 5845; Paper is Funded by the Knowledge for Change Program (KCP). World Bank, Washington, DC, USA.

Gow JA and Manning CD (1999). Development of a photovoltaic array model for use in power-electronics simulation studies. IEEE Proceedings-Electric Power Applications, 146(2): 193-200.

Jang JSR (1991). Fuzzy modeling using generalized neural networks and kalman filter algorithm. In the 9th National Conference on Artificial Intelligence, Anaheim, CA, USA, 91: 762-767.

Jang JSR (1993). ANFIS: adaptive-network-based fuzzy inference system. IEEE Transactions on Systems, Man, and Cybernetics, 23(3): 665-685.

KACARE (2016). Hail college of technology station. Solar Resource Reports for King Abdullah City for Atomic and Renewable Energy: As Part of the Renewable Resource Monitoring and Mapping (RRMM) Program, King Abdullah City for Atomic and Renewable Energy, Government agency, Saudi Arabia.

Kumari JS and Babu S (2011). Comparison of maximum power point tracking algorithms for photovoltaic system. International Journal of Advances in Engineering and Technology, 1(5):133–148.

Li J and Wang H (2009). Maximum power point tracking of photovoltaic generation based on the fuzzy control method. In the International Conference on Sustainable Power Generation and Supply, IEEE, Nanjing, China: 1-6. https://doi.org/10.1109/SUPERGEN.2009.5348168

Liu C, Wu B, and Cheung R (2004). Advanced algorithm for MPPT control of photovoltaic systems. In the Canadian solar buildings conference, Montreal, Québec, Canada: 20–24.

Lokanadham M and Bhaskar KV (2012). Incremental conductance based maximum power point tracking (MPPT) for photovoltaic system. International Journal of Engineering Research and Applications, 2(2): 1420-1424.

Mirbagheri SZ, Mekhilef S, and Mirhassani SM (2013). MPPT with Inc. Cond method using conventional interleaved boost converter. Energy Procedia, 42: 24-32.

Pierre G, Gilbert S, and Carlos O (2012). Grid-connected PV array. The Mathworks, Hydro-Quebec Research Institute (IREQ) and Shripad Chandrachood, Varennes, Canada.

Singh R and Pandit M (2013). Controlling output voltage of photovoltaic cells using ANFIS and interfacing it with closed loop boost converter. International Journal of Current Engineering and Technology, 3(2): 417-423.

Takun P, Kaitwanidvilai S, and Jettanasen C (2011). Maximum power point tracking using fuzzy logic control for photovoltaic systems. In the International MultiConference of Engineers and Computer Scientists, Hong Kong, 2: 978-988.

Villalva MG, Gazoli JR, and Ruppert Filho E (2009). Modeling and circuit-based simulation of photovoltaic arrays. In the Brazilian Power Electronics Conference, IEEE, Bonito-Mato Grosso do Sul, Brazil: 1244-1254. https://doi.org/10.1109/COBEP.2009.5347680

Wu YE, Shen CL, and Wu CY (2009). Research and improvement of maximum power point tracking for photovoltaic systems. In the International Conference on Power Electronics and Drive Systems, IEEE, Taipei, Taiwan: 1308-1312. https://doi.org/10.1109/PEDS.2009.5385787

Yousef HA (1999). Design and implementation of a fuzzy logic computer-controlled sun tracking system. In the IEEE International Symposium on Industrial Electronics, IEEE, Bled, Slovenia, 3: 1030-1034. https://doi.org/10.1109/ISIE.1999.796768

Zhou W, Yang H, and Fang Z (2007). A novel model for photovoltaic array performance prediction. Applied Energy, 84(12): 1187-1198.