Intelligent Controller to Extract Maximum Power From Solar Park

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***Abstract*—A global shortage of conventional fuels and high costs have led major energy market players toward the greater use of renewable energy sources. The Kingdom of Saudi Arabia (KSA), which has a major share in the oil market, has started working to integrate solar-based electric power into the national grid, enabling KSA to move toward eco-friendly and cheaper electricity while also maintaining a large share of the oil market.**

This paper discusses a practical technique for harvesting the maximum power from a prospective, large photovoltaic (PV) system, also known as Solar Park, in KSA. The idea is based on tracking the maximum power point from the nonlinear output characteristics of the PV system. An intelligent technique, adaptive neuro-fuzzy inference system (ANFIS), is used to build the maximum power point tracking (MPPT) controller that is tuned to extract the maximum power from the PV system under different ambient conditions. A small test system has been developed and simulated using a real-time digital simulator (RTDS), dSPACE, and MATLAB/Simulink to demonstrate the effectiveness of the proposed technique in comparison with the conventional algorithm of incremental conductance.

I. Introduction

Of the various renewable energy sources available, solar energy has proven to be the most promising and reliable. A photovoltaic (PV) system provides the most direct method to convert solar energy into electrical energy without any rotating electrical machinery. In 2011, more than 69 GW of PV power were installed worldwide with a generation capacity of 85 TWh per year [1]. Given the ongoing global oil crisis, the importance of producing electrical energy from solar power has been recognized in the Middle East, especially the Kingdom of Saudi Arabia (KSA). A research report published in 2011 determined that if KSA does not take serious measures to harvest solar energy, it will become a net energy importer by 2038 [2].

A Global Horizontal Irradiation map based on the period from 1999 to 2011 shows that the mean solar power potential of KSA is 2,200 kWh/m^2 [3]. As of 2012, KSA had only 0.003 GW of installed solar capacity; however, KSA decision makers realized the need and potential of their country and laid out plans to install 24 GW of renewable energy by 2020 and 54 GW by 2032, based primarily on solar energy [4]. For KSA to shift from conventional energy resources to solar energy, their solar plants must be built efficiently so as to extract the maximum possible electric power out of the solar energy.

The output characteristics of a PV array are highly nonlinear and have one peak point called the maximum power point (MPP). This optimum point is vulnerable to changes in irradiation and temperature, and these conditions vary constantly over time, which leads to the MPP changing. Therefore, MPP tracking (MPPT) controllers are used to trail the optimum point and to harvest the maximum possible power from the PV array.

Many MPPT methods, online and offline, have been presented in the literature, and a comprehensive comparison of these method is provided by [5] and [6]. These works identify serious drawbacks in the identified online methods, such as slow tracking of the MPP, fluctuations around the MPP in the steady state, and a failure to track the MPP in rapidly changing atmospheric conditions. All of these factors cause a considerable amount of power loss. The problem of tracking in rapidly changing conditions has been solved by incremental conductance, which works on the principle of incrementally comparing the ratio of instantaneous conductance with the derivative of conductance [7]. However, this method has tradeoffs similar to other online methods.

Offline methods include open-circuit voltage, short-circuit current, and artificial intelligence-based (AI-based) methods [8] [9]. Open-circuit voltage and short-circuit current are the simplest and most accurate methods, but they are unable to provide the true MPP because of the approximations they employ. AI-based methods are the most efficient methods because AI has the ability to deal with nonlinear systems [10]. Particle swarm optimization as an intelligent technique has been employed to find the MPP and reduce the fluctuations in the steady state [11]. A fuzzy inference system (FIS) can be used to fuzzify the rules of the hill climbing method [12], and an artificial neural network (ANN) is employed in [13]. All of these works demonstrate a substantial improvement in tracking the MPP; however, none of them completely eliminate the problems.

A new AI technique proposed in [14] is believed to have better performance than existing AI methods. It combines attributes of FIS and ANN to create a powerful AI technique known as adaptive neuro-fuzzy inference system (ANFIS) [15]. To build an ANFIS-based MPPT controller, the major challenge lies in gathering a large amount of training data. Actual field data for training an ANFIS-based MPPT are used in [16]; however, several problems are associated with the data (i.e., it does not cover a wide dynamic range, it is only appropriate for a particular geographical location, and gathering the large amount of data required for better ANFIS performance is a very time-consuming task). An easier method for obtaining training data is by simulating the PV model. In

[17], a working ANFIS-based MPPT controller is shown with a single-stage power converter topology (i.e., with the inverter only).

In this paper, a novel MPPT controller is proposed and developed based on the ANFIS with training data extracted from a precise PV model. Unlike in [17], a two-stage topology is used to provide flexibility in designing the control architecture because this offers more control variables and multiple control objectives can be achieved. A two-stage scheme also offers further advantages by providing a constant dc-link voltage to the inverter that is especially beneficial during temperature variations because temperature changes affect the PV output voltage considerably. The proposed controller hybridizes the principles of FIS and ANN. Testing results show that the proposed ANFIS-based MPPT controller can overcome the shortcomings of conventional methods and can track the MPP in a shorter time with fewer fluctuations. The effectiveness of the proposed ANFIS-based MPPT controller is shown experimentally by using real-time digital simulator (RTDS) technologies to simulate a PV system in real time and by using dSPACE to act as the proposed ANFIS-based MPPT controller.

Section II of this paper describes the electrical modeling of PV panels and a PV array based on a five-parameter model. The proposed ANFIS-based MPPT controller is explained in Section III. The experimental setup is described in Section IV, and the results and discussion are in Section V. Section VI concludes the paper.

II. PV Solar Park Modeling

A. PV Panel Modeling

This study uses an efficient five-parameter PV model, as shown in Fig. 1.

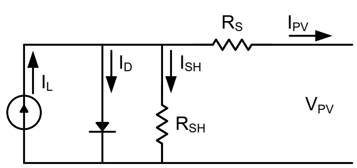

Fig. 1. Equivalent electric circuit of a PV device

This model requires the values of the following five unknown parameters:

I_L is the light-generated current.

I_0 is the reverse saturation current.

R_S is the series resistance.

R_{SH} is the shunt resistance.

a is the diode-modified ideality factor.

Using Kirchhoff's current law, the following relationship is found:

$$I = I_L - I_D - I_{SH} \tag{1}$$

$$I = I_L - I_0\left\{\exp\left[\frac{(V + I \bullet R_S)}{a}\right] - 1\right\} - \frac{V + I \bullet R_S}{R_{SH}} \tag{2}$$

In these equations, I and V represent the current and voltage generated from the PV panel, respectively. These characteristics of the PV panel are governed by the five parameters previously defined (I_L, I_0, R_S, R_{SH}, and a). When the values of these parameters are known, (2) can be solved using an efficient numerical technique, like the Newton-Raphson method. With different atmospheric conditions, these parameters have different values that can be calculated using the following model translational equations:

$$a = a_{ref}\left(\frac{T_C}{T_{C,ref}}\right) \tag{3}$$

$$I_L = \left(\frac{S}{S_{ref}}\right)\left[I_{L,ref} + \mu_{I,SC}\left(T_C - T_{C,ref}\right)\right] \tag{4}$$

$$R_{SH} = R_{SH,ref}\frac{S_{ref}}{S} \tag{5}$$

$$R_S = R_{S,ref} \tag{6}$$

$$\frac{I_0}{I_{0,ref}} = \left(\frac{T_C}{T_{C,ref}}\right)^3 \exp\left(\left(\frac{N_S \bullet T_{ref}}{a_{ref}}\right) \bullet \left(\frac{E_{G,ref}}{T_{ref}}\middle| - \frac{E_G}{T}\right|\right)\right) \tag{7}$$

$$\frac{E_G}{E_{G,ref}} = 1 - C\left(T - T_{ref}\right) \tag{8}$$

where:

S is the solar radiation of the PV panel.

T_C is the temperature of the PV panel.

$\mu_{I,SC}$ is the coefficient of the short-circuit current (provided by the manufacturer).

N_S is the number of cells in the panel (provided by the manufacturer).

E_G is the band-gap energy of the PV cell material.

$C = 0.0003174$ [8].

Quantities with the subscript *ref* represent their values at the standard test condition (STC).

B. PV Array Modeling

Large PV power stations are composed of series- and parallel-connected PV panels to increase PV power output. The output current relationship of a PV array having N_{SS} series-connected and N_{PP} parallel-connected PV panels can be given by (9) and (10).

$$I = N_{PP} \bullet I_L - N_{PP} \bullet I_0\left\{\exp\left[\frac{(V + I \bullet R_S \bullet \mathbb{N})}{N_{SS} \bullet a}\right] - 1\right\} - \left(\frac{V + I \bullet R_S \bullet \mathbb{N}}{R_{SH} \bullet \mathbb{N}}\right) \tag{9}$$

$$\mathbb{N} = \frac{N_{SS}}{N_{PP}} \tag{10}$$

The relationship of PV array parameters with the PV panel parameters is given in [16] and shown in Table I.

TABLE I
ARRAY PARAMETER VALUES IN RELATION WITH PANEL PARAMETERS

Panel Parameter	Modified Panel Array Parameter	Model Parameter	Modified Model Array Parameter
V_{OC}	$V_{OC} \bullet N_{SS}$	I_L	$I_L \bullet N_{PP}$
I_{SC}	$I_{SC} \bullet N_{PP}$	I_0	$I_0 \bullet N_{PP}$
V_{MP}	$V_{MP} \bullet N_{SS}$	R_S	$R_S \bullet (N_{SS}/N_{PP})$
I_{MP}	$I_{MP} \bullet N_{PP}$	R_{SH}	$R_{SH} \bullet (N_{SS}/N_{PP})$
n	$n \bullet N_{SS}$	a	$a \bullet N_{SS}$

III. PROPOSED ANFIS-BASED MPPT CONTROLLER

A. ANFIS Structure and Learning Process

ANFIS is based on a Sugeno-type FIS hypothesis. It possesses the learning capabilities of neural networks to improve the performance of an intelligent system by means of *a priori* information. ANFIS creates a fuzzy system and tunes the parameters of the membership function by using certain input-output data sets. Like a neural network, ANFIS also has a network-type structure and maps the input-output data set using the parameters of fuzzy membership functions. Fig. 2 demonstrates a simple ANFIS architecture based on the two-rule Sugeno system with two inputs (*x* and *y*) and a single output (F).

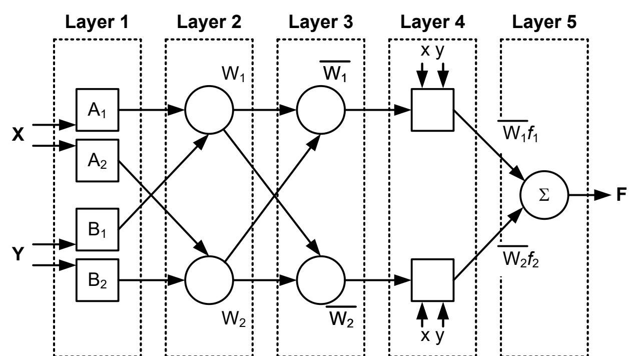

Fig. 2. ANFIS structure

Various learning methods have been proposed [17]. The method used in this study is based on a hybrid learning algorithm that employs a combination of back propagation and least-squares estimation (LSE) to optimize the premise and consequent parameters [13]. This method uses two pass learning algorithms: a forward pass using LSE and a backward pass using back propagation.

B. Application of ANFIS for MPPT

Because the output characteristics of a PV system are highly nonlinear, AI techniques are widely used to improve the efficiency of MPPT controllers. Fuzzy logic can transform linguistic and heuristic terms into numerical values and numerical values into linguistic terms using membership functions and fuzzy rules. A neural network can map the input-output nonlinear functions, but it does not have a heuristic nature. Combining FIS with ANN to build an ANFIS system balances the shortcomings of one system with the advantages of the other.

To design an MPPT controller using ANFIS, the first task is to gather the input-output data set for training the system. These training data are generated using the PV model developed in [18]. A step-by-step data generation process is illustrated in the flowchart shown in Fig. 3.

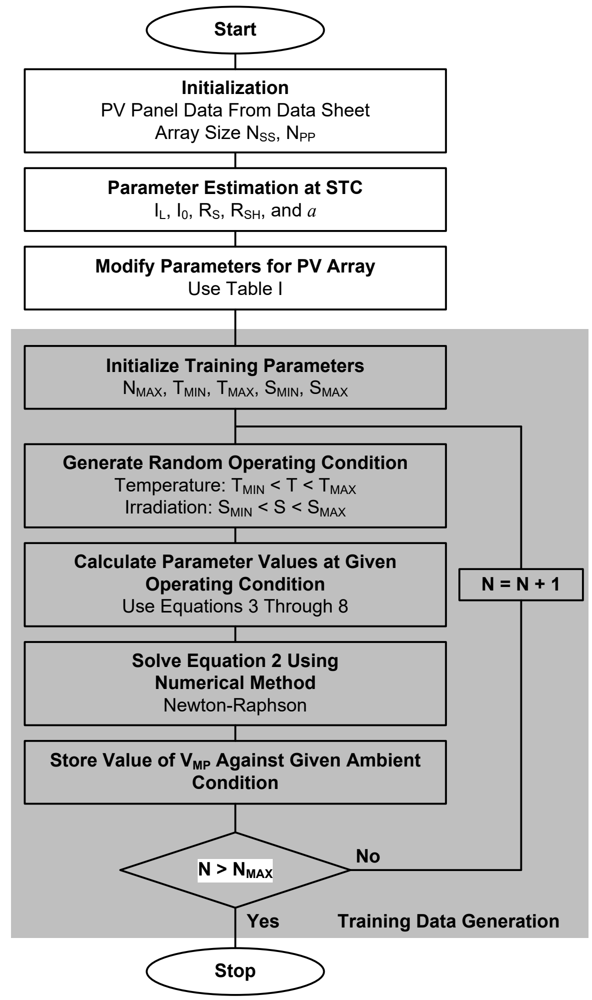

Fig. 3. Proposed method to generate input-output data set for ANFIS training

The first step in developing the data set is to estimate the values of the five unknown parameters for the PV panel under consideration. These values are then transformed for the PV array using Table I. After that, the following training parameters are initialized:

N_{MAX} is the number of training data points.

T_{MIN} is the minimum temperature.

T_{MAX} is the maximum temperature.

S_{MIN} is the minimum irradiation.

S_{MAX} is the maximum irradiation.

T_{MIN}/T_{MAX} and S_{MIN}/S_{MAX} represent the ranges of temperature and irradiation, respectively, and can be specified for the geographical location where the PV array is installed.

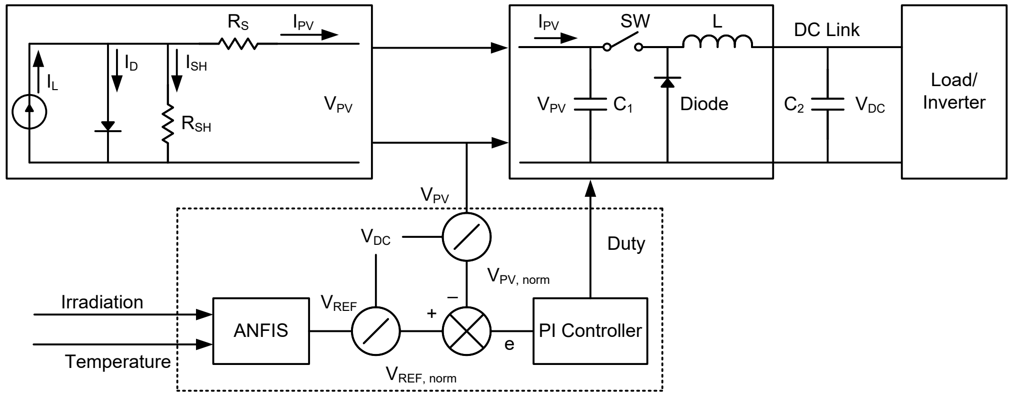

Fig. 4. PV system equipped with the proposed ANFIS-based controller

The arrangement of the proposed ANFIS-based MPPT controller is shown in Fig. 4. The inputs of the proposed controller are the ambient conditions (i.e., the irradiation and temperature) and its output is the reference voltage (V_{REF}), which is normalized using the dc-link voltage (V_{DC}). The normalized reference voltage ($V_{REF,\ norm}$) is fed back to the voltage control loop. The proportional integral (PI) controller maintains the output voltage of the PV array (V_{PV}) to the reference optimal voltage by adjusting the duty ratio of the dc-dc converter, resulting in maximum power extraction.

IV. Hardware-in-the-Loop Setup

An RTDS and a dSPACE board were used to create a hardware-in-the-loop experimental arrangement to measure the performance of the ANFIS-based MPPT controller.

The RTDS employs parallel processing to analyze electromagnetic transients in real time with high accuracy and quality. In this study, it was used to emulate a complete PV installation (i.e., solar park), including the PV array, dc-dc converter, PI controllers, and dc-link capacitor. Because the process of MPPT involves the continuous switching of the dc-dc converter, the RTDS is a good option for its analysis. It is equipped with two Giga-Transceiver (GT) cards (GT Analogue Output [GTAO] and GT Analogue Input [GTAI]) used to make the hardware-in-the-loop setup with the MPPT controller.

The dSPACE board is a digital signal processing microcontroller based on a floating point processor, and the proposed ANFIS-based MPPT controller is designed and implemented over it. It also contains analog input (ADC) and analog output (DAC) interfaces to connect with the RTDS. These interfaces convert the signals from analog to digital and digital to analog, respectively. Fig. 5 shows the block diagram of the complete hardware-in-the-loop experimental setup.

As stated previously, irradiation and temperature are the inputs for the proposed MPPT controller. These signals are taken from the RTDS GTAO card and provided to the dSPACE board as an analog input. The ANFIS-based MPPT processes these inputs and generates a set point of V_{REF} as an output. This set-point analog signal is wired to the RTDS using the GTAI card and is used by the PI regulator in the RTDS to produce the desired duty cycle for the dc-dc converter.

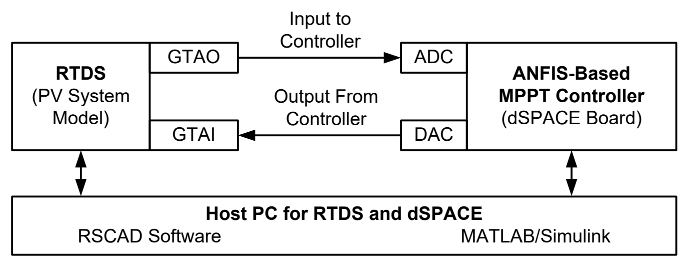

Fig. 5. Hardware-in-the-loop block diagram

V. Controller Validation

A. PV Solar Park Specification

The solar park was emulated by the RTDS and used to test the effectiveness of the ANFIS-based MPPT controller. The PV array comprises 20 parallel-connected and 50 series-connected PV panels (N_{PP} = 20 and N_{SS} = 50), and its specification is shown in Table II.

TABLE II
SPECIFIED PV PANEL PARAMETERS AT STC

Panel Parameters From Data Sheet	Panel Parameter Values	Estimated Model Parameters	Estimated Model Values
V_{OC} (V)	21.7	I_L(A)	3.35
I_{SC} (A)	3.35	I_0 (A)	1.7053e-05
V_{MP} (V)	17.4	R_S (Ω)	0.00477
I_{MP} (A)	3.05	R_{SH} (Ω)	3.9601e+04
n	36	*a*	1.78044

B. ANFIS-Based MPPT Controller Design

The design of the ANFIS-based MPPT controller required an input-output data set. In this study, it was generated using an efficient PV model, as discussed previously. In the process of generating the data set, the selection of the training parameters was vital because they have a direct impact on the performance of the controller. In this study, the training parameters were N_{MAX} = 1000, T_{MAX} = 80°C, T_{MIN} = –20°C, S_{MAX} = 2000 W/m^2, and S_{MIN} = 0 W/m^2. These diverse and dynamic ranges of irradiation and temperature enable the controller to perform well even under uncertain and extreme atmospheric conditions.

Generalized bell membership functions were used to build the proposed controller in MATLAB/Simulink. The efficiency of various membership functions was compared using the training root-mean-square error (RMSE), and three membership functions were selected. A total of 300 epochs were used for ANFIS training, which decreased the RMSE to 0.8, as shown in Fig. 6.

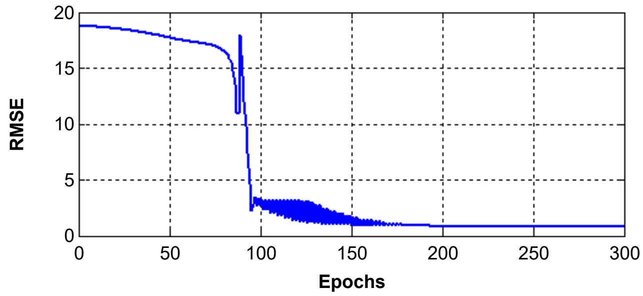

Fig. 6. RMSE versus epochs for the ANFIS-based MPPT controller

C. Results and Discussion

A performance comparison was carried out with a conventional MPPT controller using the incremental conductance technique. The experimental setup detailed in Section IV was used to conduct this test in which the irradiation level of the PV solar park was disturbed and the performance of both MPPT methods (conventional and proposed) was compared. In this test, the irradiation level was increased from low (500 W/m^2) to normal (1,000 W/m^2) to analyze the effectiveness of the controllers under a drastic change in environmental conditions. Fig. 7 shows the PV curve for normal and low irradiation at the solar park.

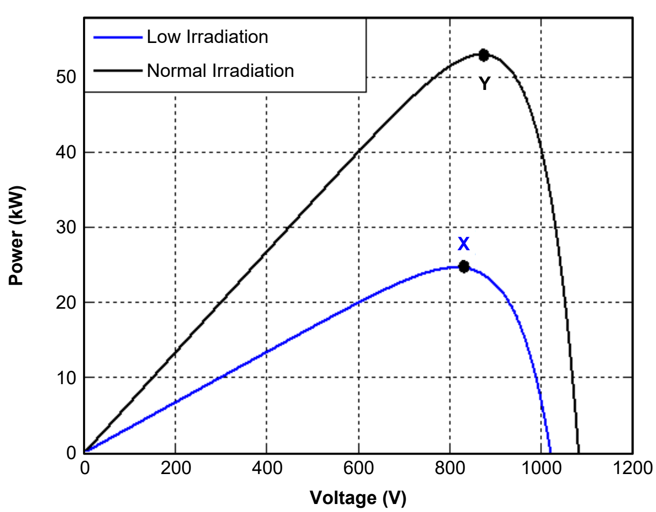

Fig. 7. PV curve under normal and low irradiation

An RTDS-based nonlinear time-domain simulation was performed with the proposed and conventional MPPT controllers. For the conventional method (incremental conductance), a fixed perturbation step size was used and was selected based on a tradeoff between speed in the transition state and oscillations in the steady state.

The solar park power output (P_{PV}) using both controllers is shown in Fig. 8. It shows that the proposed controller has less oscillation and can reach the steady state earlier than the conventional method. Fig. 9 shows the PV solar park output voltage (V_{PV}), current (I_{PV}), and duty cycle the for dc-dc converter. These figures and results demonstrate the effectiveness of the proposed controller versus a conventional controller.

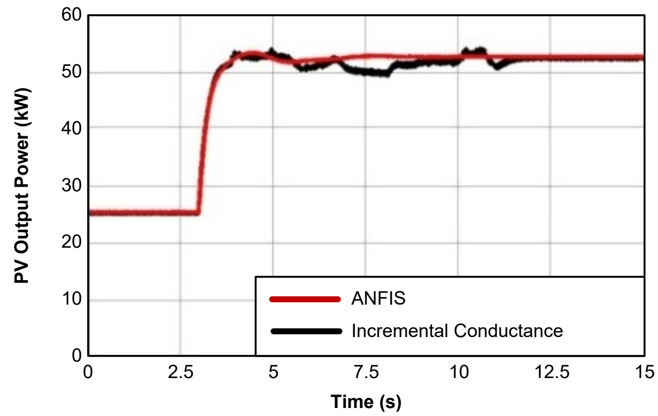

Fig. 8. PV solar park output power

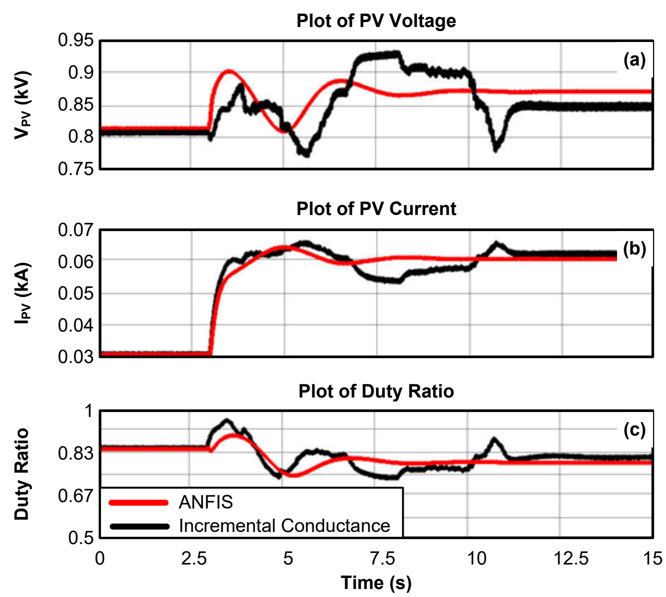

Fig. 9. PV solar park voltage (a), current (b), and duty cycle (c)

From these experimental results, it can be inferred that the proposed controller is faster than the conventional controller in a transitional state and has less fluctuation during a steady state. These factors result in less power loss and more power output from the solar park.

Software simulation was also carried out for the same system in a MATLAB/Simulink environment, and these results were compared with the experimental results to validate the performance of the proposed controller. Fig. 10a shows the PV solar park output power (P_{PV}) and compares the simulation and experimental results for the MPPT using the proposed controller. Similarly, Fig. 10b and Fig. 10c show comparisons of the solar park output voltage (V_{PV}) and current (I_{PV}), respectively. All of these figures show the similarity between the experimental and simulation results and validate the accuracy of the proposed controller.

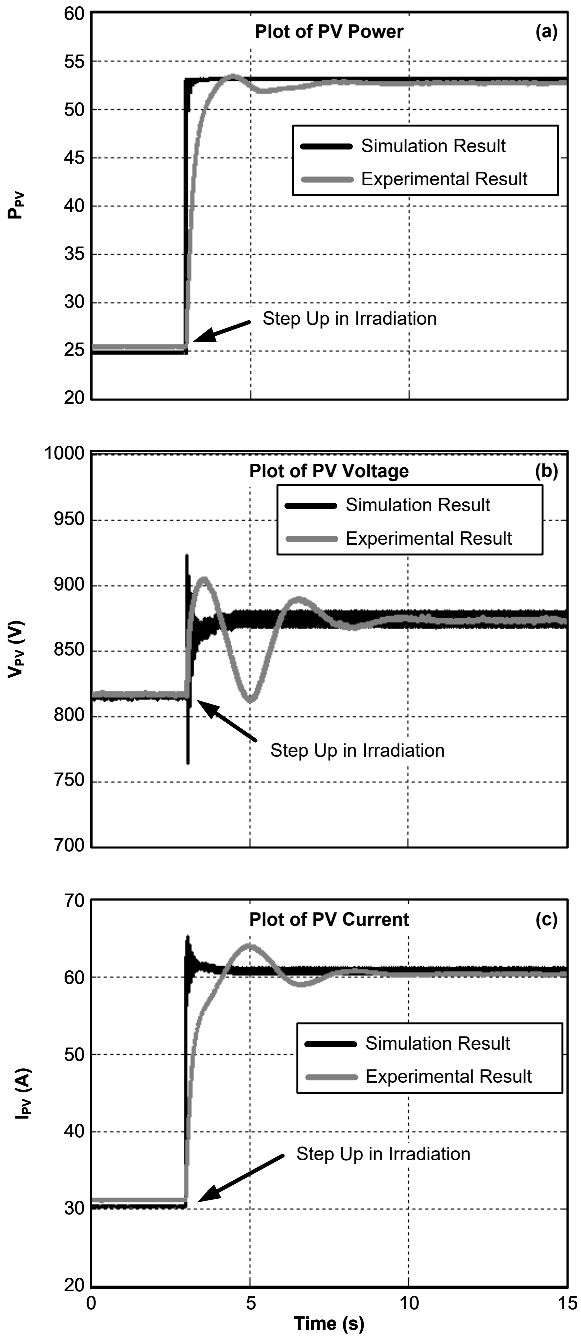

Fig. 10. Comparison of experimental and simulation results of solar park power output (a), voltage (b), and current (c)

VI. Conclusion

The use of a real-time experimental setup and the analysis of the obtained results clearly demonstrate the efficiency of the proposed technique. Although, the technique was analyzed using a prototype setup, the modular nature of PV panels allows for the use of the proposed technique for large solar parks. The proposed technique can be used at the initial stages of a project to identify the parameters for the MPPT controller and later on for monitoring the performance of the controller and adjusting the parameters as needed to ensure that maximum energy is harvested from the solar array throughout the year.

The need for KSA to shift from conventional oil-based energy to solar power requires that the installed solar parks be able to extract the maximum electrical energy. The proposed technique can help energy experts meet this requirement by making appropriate decisions before the installation of the solar parks. This will reduce the likelihood of poor efficiency after project completion.

VII. Acknowledgment

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IX. BIOGRAPHIES

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