



NOVEL SOLAR PHOTOVOLTAIC EMULATION FOR VALIDATING THE MAXIMUM POWER POINT ALGORITHM AND POWER CONVERTER

MEENAKSHI SUNDARAM ULAGANATHAN¹, RATHINAM MUNIRAJ², RADHAKRISHNAN VIJAYANAND³, DURAIRAJ DEVARAJ⁴

Keywords: Neural networks; Solar array emulator; Diode-based solar array emulator; Programmable dc power source; Perturb and observe maximum power point algorithm.

The photovoltaic (PV) source emulator plays an essential role in evaluating the performance of solar PV arrays, maximum power point (MPPT algorithms), power converters, and control algorithms in the rapidly growing field of solar power generation. This paper presents a novel neural network (NN)-based solar array emulator (SAE) for emulating PV array dynamic characteristics. The proposed SAE reference model developed using NN, replicates PV array characteristics with a programmable dc power source's support under varying environmental conditions. A 640 W stand-alone PV system is designed and tested using the proposed SAE to validate its performance under various environmental conditions. The performance of the NN-based SAE with the MPPT algorithm is evaluated and compared to the conventional diode-based SAE. The results showed that the proposed NN-based SAE had good accuracy in emulating the dynamic characteristics of the PV array and was faster in execution than the conventional diode-based SAE. The output results of the developed NN-based SAE demonstrate its potential for evaluating MPPT algorithms and power converters.

1. INTRODUCTION

Solar power generation (SPG) is a promising alternative to traditional power sources. The PV array in SPG is critical to evaluate, but its non-linear nature makes it challenging under varying environmental conditions [1,2]. Solar array emulators (SAEs) are a viable solution for accurately evaluating SPG [3]. SAEs are programmable dc sources that mimic the PV array's behavior under controlled conditions for repeatable assessments [4]. An SAE includes a reference model, tracking algorithm, and power stage for accurate SPG evaluation.

The reference model mimics PV array characteristics [5]. The most discussed reference model in the literature is the electrical equivalent reference model that uses Kirchhoff's circuit laws to calculate the PV source characteristics equation [6]. The single and double-diode models with series and shunt resistance are the commonly discussed electrical equivalent models [7,8]. The internal parameters of these models are estimated by measuring the PV source's operating parameters using optimization techniques [9]. However, incorrect operating point measurement can affect the PV model's accuracy.

The reference tracking algorithm plays a crucial role in accurately tracking the operating voltage and current of the SAE. One commonly used tracking algorithm is the direct referencing method [10,11], which employs an iterative approach to determine the operating points of the SAE using either voltage or current input. The difference between the expected and actual output of the SAE determines the number of iterations required. Alternatively, the resistance comparison algorithm [12] tracks the output voltage and current of the SAE using resistance as an input.

The power stage of a PV SAE is responsible for converting the emulated electrical characteristic into real power [13]. However, a complex reference tracking algorithm and adaptive controller used in a buck converter-based SAE proposed in [14] may lead to stability and accuracy issues. Moreover, digital controllers like field-programmable gate arrays or digital signal processors must implement these algorithms, resulting in lengthy sampling times and inaccurate control responses. In contrast, power supply-based SAEs

analyzed in [15] employ simple analog controllers and resistance comparison-based reference tracking algorithms, which improve repeatability and output stability and reduce complexity during hardware implementation.

This paper proposes a novel SAE that utilizes experimental data from an actual PV array to enhance the reference model. The proposed SAE incorporates online load tracking as a simple reference tracking algorithm that eliminates the requirement for an additional control loop to monitor the SAE's output voltage and current, thereby improving stability and dynamic response. The programmable dc power source is the SAE power stage, mimicking the PV array characteristics with analog controller support. The NN-based SAE can replicate the PV array's dynamic characteristics, making it a suitable tool for emulating it and evaluating the maximum power point tracking (MPPT) controllers and power converters in solar PV systems.

The paper is structured as follows: section 2 discusses the proposed neural network-based solar array emulator (NN-based SAE), covering its components, data-driven modeling, and the innovative online load-tracking algorithm. Section 3 focuses on developing the NN-based SAE's reference model, emphasizing multilayer feed-forward (MLFF) neural networks. Moving on to section 4, the seamless integration of the online load-tracking algorithm, highlighting its crucial role in achieving accurate emulation, is presented. Section 5 provides insights into monitoring and controlling the programmable dc power supply, offering a comprehensive understanding of the SAE's operational framework. Section 6 presents experimental results, dynamic analyses, and comparative evaluations, shedding light on the efficacy and performance of the NN-based SAE. Finally, section 7 concludes with the most significant findings.

2. DESCRIPTION OF THE PROPOSED NEURAL NETWORK-BASED SOLAR ARRAY EMULATOR (NN-BASED SAE)

Figure 1 illustrates the schematic diagram of the NN-based SAE proposed in this paper. The SAE uses a data-driven modeling approach for reference model development, which involves learning the PV array model from input and

^{1,2}P.S.R. Engineering College, Sivakasi, Tamilnadu, India, E-mails: ¹ulaganathan@psr.edu.in (Corresponding Author), ²muniraj@psr.edu.in

³Nagarjuna College of Engineering and Technology, Bengaluru, India, E-mail: rkvijayanand@gmail.com

⁴Kalasalingam Academy of Research and Education, India, E-mail: d.devaraj@klu.ac.in

output datasets from an actual PV array. The system employs an NN-based reference model that estimates the optimum PV array voltage ($V_{PV(Est)}$) and current ($I_{PV(Est)}$) using a feed-forward neural network. The NN-based reference model is developed using data collected under various environmental and loading conditions from an entire PV array. The inputs to the NN model are irradiation, temperature, and load, which accurately estimate the PV array voltage and current.

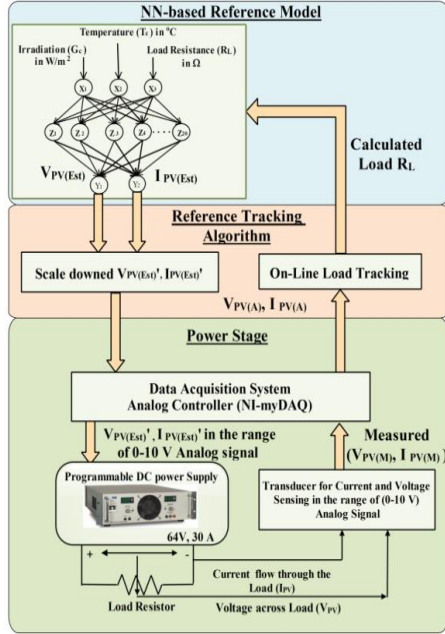


Fig. 1 – Schematic diagram of the Proposed NN-based SAE.

The proposed SAE integrates the reference model into a programmable dc power supply through an online load-tracking algorithm. The reference tracking algorithm uses the NN-estimated operating parameters of the SAE as the control signal and the load connected to the SAE as the feedback signal. The NN model outputs are converted into analog signals ($V_{PV(Est)'}$ and $I_{PV(Est)'}$), which are used as the control signal to reproduce the dynamics of the SAE reference model using the SAE power stage.

The SAE power stage receives the $V_{PV(Est)'}$ and $I_{PV(Est)'}$ through the analog controller platform called National Instrument (NI)-myDAQ and generates linearized emulated operating points of the NN-based SAE, namely voltage (V_{PV}) and current (I_{PV}) proportional to it. These emulated operating values are measured across the load feedback into the NN model to track SAE operation using the online load tracking algorithm. The proposed SAE is developed in three stages: reference model development using an Artificial Neural Network, online load tracking integration, and monitoring and controlling the programmable dc power supply.

3. DEVELOPMENT OF REFERENCE MODEL USING ARTIFICIAL NEURAL NETWORK FOR SAE

In this work, a multilayer feed-forward (MLFF) neural network is employed to estimate the optimum PV array voltage $V_{PV(Est)}$ and current $I_{PV(Est)}$. MLFF neural network is an artificial neural network (ANN) comprising cascaded neuron layers, including input, hidden, and output layers. Each neuron's output is the sum of its weighted inputs passed through a non-linear activation function [16].

The proposed MLFF NN structure for estimating the $V_{PV(Est)}$ and $I_{PV(Est)}$ of the PV array is depicted in Fig. 2. The

MLFF NN has two stages: development and operation. In the development stage, real-time experimental data is collected from a PV array and divided into training and test data. The training data is utilized to develop the network, whereas the test data is used to evaluate the performance of the developed network. During training, the MLFF maps the relationship between the input variables (irradiation, temperature, and loading conditions) and output variables ($V_{PV(Est)}$ and $I_{PV(Est)}$) using the connecting weights. The training data set consists of input and corresponding output variable samples.

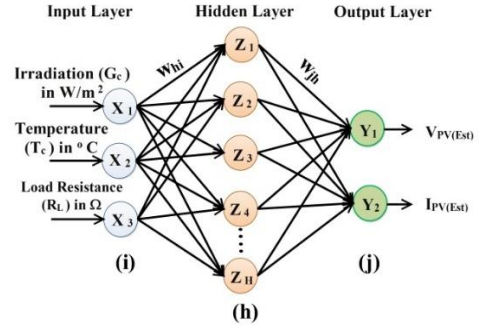


Fig. 2 – Multilayer Feed-Forward Network for estimating PV array output voltage $V_{PV(Est)}$ and current $I_{PV(Est)}$.

During the MLFF NN training process, weights in the network are randomly assigned, and the backpropagation algorithm is used to adjust them. The backpropagation algorithm performs feed-forward propagation of input, error backpropagation, and weight updating. The network output is determined using a summation function expressed by eq. (1). Mean square error (MSE) is used to evaluate the training process effectiveness and is expressed by eq. (2). The weight adjustment process continues during training until the set learning goal is achieved

$$y_j^k = f(\text{net}_j^k) \Rightarrow f \left[\sum_{j=1}^n w_{jk} z_h^k + b_j \right]. \quad (1)$$

The error function is:

$$E^k = \frac{1}{2} \sum_{j=1}^m (d_j - y_j^k)^2, \quad (2)$$

where j and h denote the indices of output and hidden layer neurons, respectively, represent the output of the h^{th} hidden layer neuron. n and m represent the number of input and output variables. w_{jh} denotes the connection weight between the h^{th} neuron and the j^{th} neuron, and b_j and k represent the bias constant and iterations. The weight adjustment process is continued during training until it reaches the set learning goal.

After the training process, the developed network is evaluated for its estimation performance using the test data. The updated weights from the training process enable the network to provide an output that matches the expected values. The developed NN model is tested using a separate set of testing data following the training stage. Upon completing the training and testing stages, the network can estimate $V_{PV(Est)}$ and $I_{PV(Est)}$ for unknown input values.

4. INTEGRATION OF ONLINE LOAD TRACKING ALGORITHM

The online load tracking algorithm calculates the load connected to the SAE power stage and provides feedback to the NN-based SAE reference model. V_{PV} and I_{PV} output of

the SAE is measured and scaled down into $V_{PV(M)}$, and $I_{PV(M)}$ using a voltage transducer 0 – 5 V range and acquired using the NI-myDAQ. The acquired values are then collected in LabVIEW and scaled into the actual measured PV array voltage $V_{PV(A)}$ and current $I_{PV(A)}$. The algorithm monitors $V_{PV(A)}$ and $I_{PV(A)}$ and computes load resistance ($R_L = V_{PV(A)}/I_{PV(A)}$) online. During the initial iteration, the resistive load is fixed to the Maximum under constant irradiation and temperature. The reference model estimates the output voltage $V_{PV(Est)}$ and output current $I_{PV(Est)}$ of the PV array, which is mimicked by the SAE power stage.

The SAE power stage voltage output V_{PV} is measured across the load that equals the emulated PV array V_{OC} . The load resistance value is adjusted, the dc power supply generates different VPV values, and the corresponding I_{PV} values are measured in series with the load resistance. The updated load resistance R_L value is computed and fed back into the reference model of the NN-based SAE through the LabVIEW control and simulation loop. The emulated PV array characteristics are obtained by repeating the procedure under different environmental conditions by changing the irradiation and temperature values in the NN-based SAE. The proposed SAE is developed without iterative and sophisticated control loops to emulate the PV array. Figure 3 shows the flowchart of the online tracking algorithm integration.

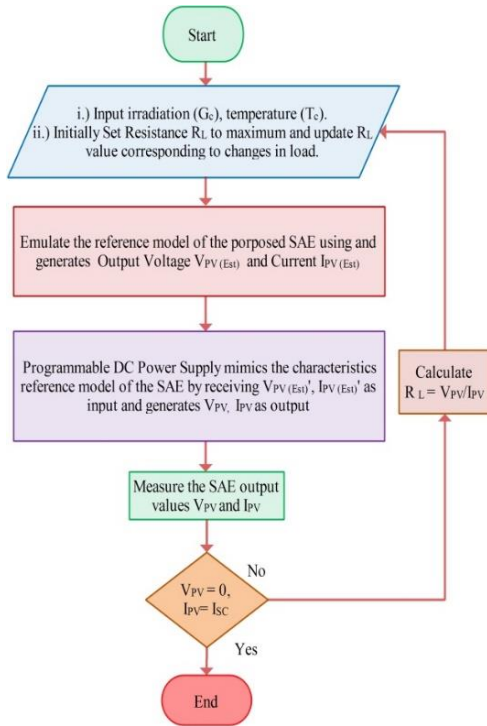


Fig. 3 – Online tracking algorithm flow chart.

5. MONITORING AND CONTROL OF PROGRAMMABLE DC POWER SUPPLY

The programmable dc power supply is monitored and controlled by using the estimated values of $V_{PV(Est)}$ and $I_{PV(Est)}$, which are scaled-down as $V_{PV(Est)}$ and $I_{PV(Est)}$ in the reference tracking algorithm stage. These scaled-down values are utilized to drive the SAE power supply with the help of the National Instrument (NI)-myDAQ, which acts as a control signal in the power stage. To ensure the accuracy of the SAE output in the reference tracking stage, an online load tracking system is integrated with the programmable dc power supply. The online load tracking system monitors the SAE operations and generates a feedback signal to the SAE reference model.

6. RESULTS AND DISCUSSION

This section describes the development of the SAE's reference model and reference tracking algorithm and the experimental analysis conducted with the developed SAE. A stand-alone PV system was implemented using the proposed SAE to perform dynamic analysis under varying irradiation levels and at STC. The execution speed of the NN-based SAE was determined through dynamic analysis. The tracking performance of the SAE was evaluated at STC and under varying irradiation levels, and the experimental results were compared with those of the diode-based SAE.

6.1. DEVELOPMENT OF REFERENCE MODEL FOR NN-BASED SAE

An NN-based reference model is developed using experimental data from an actual PV array with eight modules in a 2×4 configuration, with a peak power of 640 W. The PV module parameters are listed in Table 1. The PV array and data logging unit used to collect the data are shown in Fig. 4. Experimental data is collected from a PV array with a peak power of 640 W, directly connected to a 50 Ω rheostat for load variation. The PV array output voltage (V_{PV}) and current (I_{PV}) values are measured under different irradiation and temperature levels. An irradiation sensor measures the irradiation level and converts it to a voltage output between 0 – 1.6 V. The temperature sensor measures temperature variation between 0 – 100 °C and converts the temperature data to a voltage signal between 0–5 V. The measured values are collected using NI myDAQ. A total of 3440 datasets of irradiation, temperature level, load conditions, and PV array output voltage and current are collected, out of which 2408 datasets are used for training and the remaining for testing.

Table 1
Operating parameters of the Sukam PV module

Specifications	Value
Voltage at P_{MPP} (V_{MP})	17.35 A
Current at P_{MPP} (I_{MP})	4.61 A
Maximum Power Point (P_{MPP})	80.04 W
Short Circuit Current (I_{SC})	5.2 A
Open Circuit Voltage (V_{OC})	21.2 V



Fig. 4 – Solar PV array and its data logging unit.

A neural network with one hidden layer and three layers is developed. It takes irradiation, temperature, and load conditions as input and PV array output voltage and current as output. The number of hidden layer neurons is determined through trial and error, and tangent hyperbolic and linear activation functions are used in the hidden and output layers. The NN was trained with the Levenberg-Marquardt algorithm until it reached the MSE of 1.9×10^{-3} , using 2 408 datasets for training and 1 032 datasets for testing. The NN had 20 hidden layer neurons and achieved a testing RMSE of 0.0139 in 3 678 epochs, completing testing in 437 ms with a testing MSE of

0.0137. Figure 5 presents the estimated PV array output $V_{PV(Est)}$ and $I_{PV(Est)}$. These plots show that the developed reference model can satisfactorily estimate the $V_{PV(Est)}$ and $I_{PV(Est)}$ values, matching the PV array's V_{PV} and I_{PV} output.

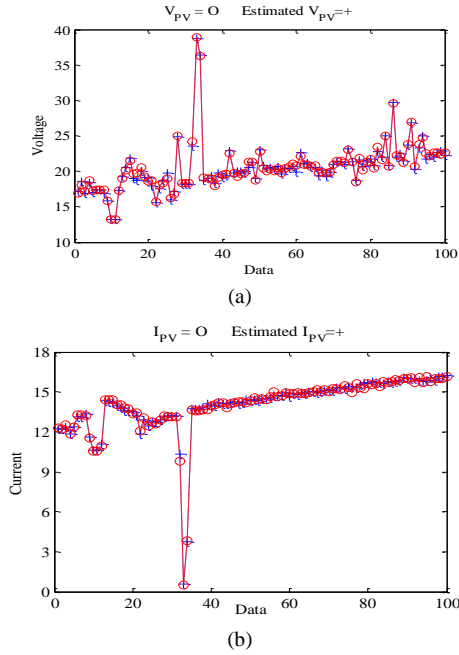


Fig. 5 – Estimated PV array output: (a) voltage $V_{PV(Est)}$, (b) current $I_{PV(Est)}$.

6.2. PERFORMANCE EVALUATION OF THE DEVELOPED REFERENCE MODEL

This study uses a PV array with a peak power output of 640 W to evaluate the NN-based SAE. As mentioned earlier, the reference model of the NN-based SAE is trained and tested in MATLAB. Following this, the MATLAB script is used to implement the trained reference model of NN-based SAE in LabVIEW.

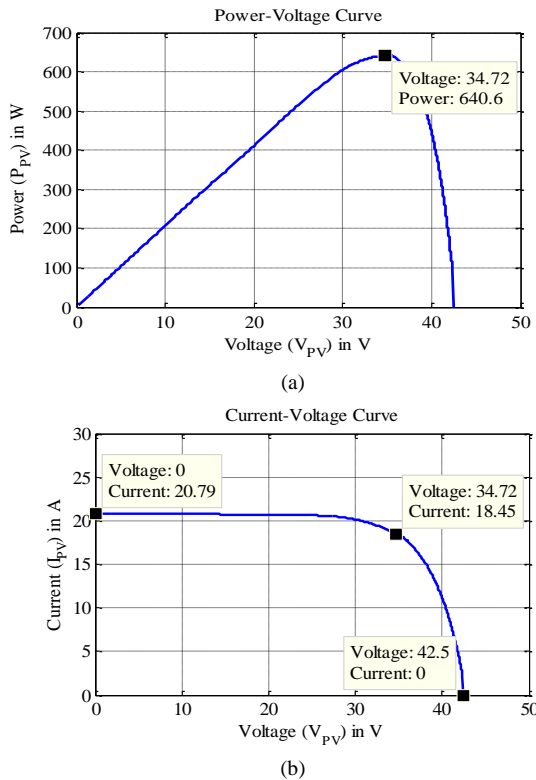


Fig. 6 – Electrical characteristics of the simulated NN-based SAE at STC a) P - V ; b) I - V .

The reference model estimates the PV array's output $V_{PV(Est)}$ and $I_{PV(Est)}$ using the input received from LabVIEW. The reference model is co-simulated in the control and simulation loop with a Runge-Kutta-1 resolver and a step size of 1 ms. The simulated SAE is analyzed at STC, *i.e.*, with an irradiation of 1000 W/m^2 and a temperature of 25°C . The characteristic curves of the simulated NN-based PV array reference model are depicted in Fig. 6. The accuracy of the NN-based SAE reference model is determined by calculating the Relative Error (RE) under STC. The RE values of the reference model for the PV array are calculated using eq. (3) tabulated in Table 2 presents 2 RE between the PV array's theoretical and reference model output.

$$RE(X) = \frac{|X_{(Theoretical)} - X_{(Simulated)}|}{X_{(Theoretical)}} \times 100\%, \quad (3)$$

where X is the PV array operating parameter.

Table 2

RE between the theoretical output and reference model output of the PV array

Parameter	Theoretical Output of PV Array	Simulated output of the PV array	RE %	
Irradiation - 1000 W/m^2 Temperature- 25°C	Open Circuit Voltage (V_{OC}) in V	42.4	42.49	0.21
	Short Circuit Current (I_{SC}) in A	20.8	20.79	0.04
	Voltage at MPP (V_{MPP}) in V	34.7	34.72	0.05
	Current at MPP (I_{MPP}) in A	18.4	18.45	0.27
	Power at MPP (P_{MPP}) in W	640.28	640.58	0.04

The RE at maximum power point (MPP) is 0.04 %, demonstrating the NN-based reference model accuracy. Thus, the developed reference model of the PV array can be used for real-time emulation.

6.3. HARDWARE IMPLEMENTATION OF REFERENCE TRACKING ALGORITHM OF THE PROPOSED SAE

The hardware setup of the proposed SAE is shown in Fig. 7.

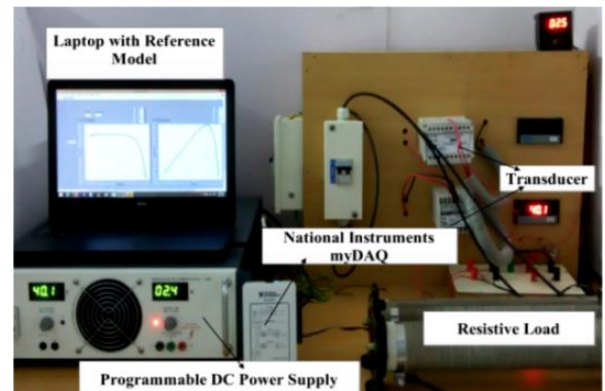


Fig. 7 – The test setup of the proposed SAE.

The proposed SAE hardware setup has a $V_{PV(EST)}$ range of $0 - 42.4 \text{ V}$ and an $I_{PV(EST)}$ range of $0 - 20.8 \text{ A}$, monitored using NI-myDAQ. The $V_{PV(EST)}$ and $I_{PV(EST)}$ outputs of the NN-based SAE are scaled down to the $0 - 10 \text{ V}$ range and sent to regulate the power stage. The voltage transducer and dc shunt measure $V_{PV(M)}$ and $I_{PV(M)}$, respectively, with the

measured values converted to the 0 – 10 V range. These measured $V_{PV(M)}$ and $I_{PV(M)}$ values are fed back to the LabVIEW environment via the NI-myDAQ analog input port-1 and port-2. The measured $V_{PV(M)}$ and $I_{PV(M)}$ values are then scaled back to the actual voltage $V_{PV(A)}$ and current $I_{PV(A)}$ values of the emulated PV array.

6.4. EXPERIMENTAL SETUP WITH MPPT CONTROLLER

An experimental setup performs dynamic analysis of the proposed SAE, like a stand-alone PV system. The hardware includes the NN-based SAE, a dc/dc converter, an MPPT controller, and a load. The experimental setup is depicted in Fig. 8. The NN-based SAE is directly connected to the boost converter and the load. The components of the boost converter are listed in Table 3.

Table 3

Boost converter components	
Component	Values
Inductance (L)	550 mH
Capacitance (C)	330 μ f
Resistance (R_{Load})	3.6 ohms
Switching Frequency	10 kHz

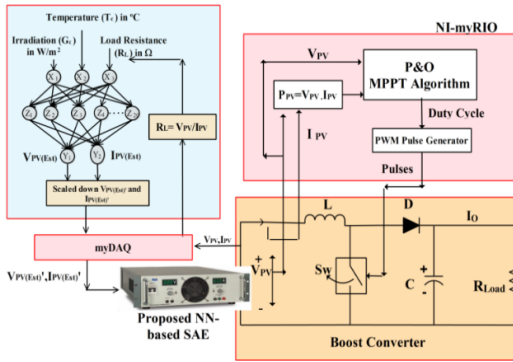


Fig. 8 – Experimental setup for dynamic analysis.

The MPPT controller is used to track the maximum power output of the proposed SAE. The perturb and observe (P&O) algorithm is adopted in this work and developed in LabVIEW, which is implemented in National Instruments-myRIO. The LabVIEW blocks of the MPPT algorithm are shown in Fig. 9. The input values of the P&O algorithm are measured at the output of the NN-based SAE prototype. In contrast, the previous V_{PV} , P_{PV} , and duty cycle values are determined using the transport delay with a 500 ms interval. Based on the switching conditions ($\Delta P_{PV}/\Delta V_{PV} > 0$), the P&O algorithm generates a duty cycle value fed into PWM port 1 of myRIO. myRIO then generates PWM pulses according to the estimated duty cycle.

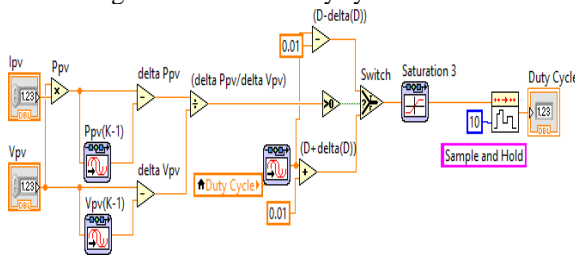
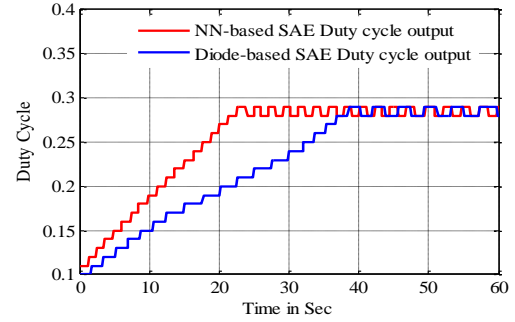


Fig. 9 – P&O MPPT algorithm blocks developed in LabVIEW.

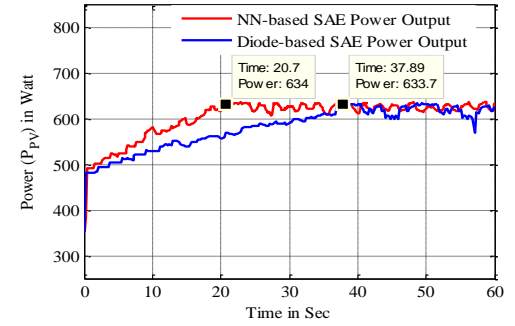
6.4.1. Dynamic analysis of the proposed sae at STC

The proposed SAE reference model was evaluated through dynamic analysis to assess its execution speed and accuracy at STC. The maximum power output of the emulated solar PV array was 641 W, with $V_{PV(Est)}$ and $I_{PV(Est)}$ estimated as 34.8 V

and 12.9 A, respectively. The P&O MPPT controller was employed to track the MPP, starting with a duty cycle perturbation of step size 0.01 and increasing the duty cycle value in steps until it reached the MPP. As depicted in Fig. 10a, the P&O algorithm tracked the maximum power of 634 W from the proposed SAE in 20.7 s. In contrast, the diode-based SAE took 37.89 s to track the maximum power of 633.7 W, as shown in Fig. 10b. Both SAEs could track the maximum power with minimal error, but the execution time of the NN-based SAE was shorter than that of the diode-based SAE.



(a)

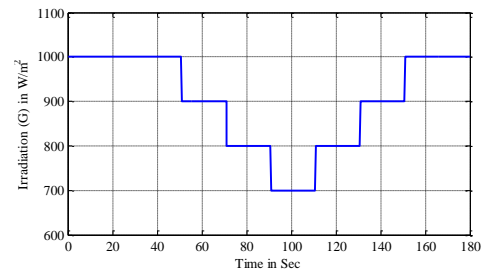


(b)

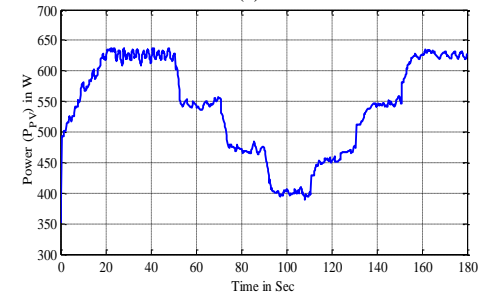
Fig. 10 – a) Duty cycle output; b) – maximum power tracked on NN-based and diode-based SAE at STC.

6.4.2. Dynamic analysis of the NN-based SAE

The performance of the NN-based SAE is evaluated under varying irradiation conditions while maintaining a constant temperature of 25°C.



(a)



(b)

Fig. 11 – a) Changes in irradiation level; b) – maximum power tracked in the NN-based SAE with P&O MPPT controller.

The irradiation level varies from 1000 W/m² to 700 W/m² in steps of 100 W/m² and then increases with an interval of 20 s. The objective is to study the behavior of the NN-based SAE under different irradiation conditions and how accurately it tracks the maximum power point. Figure 11 presents the varying irradiation levels and depicts the maximum power tracked by the P&O MPPT controller in the NN-based SAE under varying irradiation conditions.

Figure 12 shows the maximum power tracked by the P&O controller in NN-based SAE and diode-based SAE. The NN-based SAE estimates the output voltage and current of the emulated PV array. It drives the programmable dc power supply faster than the conventional diode-based SAE, which uses a diode model to calculate the output power. The NN-based SAE emulates the PV array characteristics with a maximum of 9.5 s to track the maximum power for the irradiation changes.

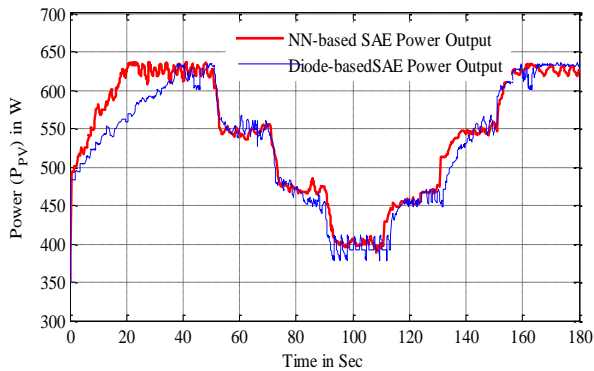


Fig. 12 – Comparison between the maximum power tracked in the NN-based and diode-based SAE using the P&O MPPT controller.

In contrast, diode-based SAE takes 15.2 s, Table 5.

Table 5

G [W/m ²]	NN-based SAE	Diode-based SAE
	Tracking time [s]	Tracking time [s]
1000	20.7	37.89
900	08.2	14.4
800	09.2	15.2
700	09.5	13.1

The accuracy of the developed SAE is evaluated by calculating the static MPPT tracking efficiency using:

$$\eta_{(\text{static MPPT})} = \frac{P_{PV(\text{out})}}{P_{PV(\text{MPP})}} \cdot 100\% \quad (4)$$

Table 6

Comparison of the power output of the emulated PV array using NN-based SAE and Diode-based SAE

G [W/m ²]	Actual P _{MPP}	NN-based SAE		Diode-based SAE	
		P _{MPP}	η_{static}	P _{MPP}	η_{static}
1000	640.32	634.0	99	633.7	98.9
900	570.20	548.2	96.1	547.6	96.0
800	501.31	465.9	92.8	459.8	91.5
700	431.85	390.9	90.4	389.9	90.2
		Avg.	94.5	Avg.	94.15

Table 6 presents the static MPPT efficiency of the NN-based and diode-based SAE under different irradiation levels. The results show that the average static efficiency of the P&O MPPT controller in the NN-based SAE is 94.5 %, while the diode-based SAE has an efficiency of 94.15 %. The above results indicate that the developed NN-based SAE can accurately emulate the characteristics of the PV array, comparable to the diode-based SAE.

7. CONCLUSION

This work proposes a novel neural network-based SAE that uses a programmable dc source. The reference model of the SAE is developed using MATLAB and experimental data from the PV array. The online tracking algorithm connects the reference model of the SAE and the dc power supply, which is programmed to mimic the PV array's behaviour using the NI myDAQ.

The dynamic analysis evaluates the developed SAE's performance in emulating the stand-alone PV system using the P&O MPPT controller. The static MPPT efficiency of the P&O MPPT controller in the NN-based SAE is 94.5%, close to that of the diode-based SAE. The developed SAE tracks the MPP in 20.7 s under STC conditions, which is faster than the Diode-based SAE. The NN-based SAE takes a maximum of 9.5 s under varying irradiation conditions. These output results show that the NN-based SAE's reference model drives the SAE power stage faster than the diode-based SAE due to the NN-based reference model, simple online tracking algorithm, and the online tracking algorithm analog controller NI-myDAQ. Therefore, the developed NN-based SAE is more suitable for emulating the PV array and validation of the MPPT algorithm and power converter.

Received on 29 June 2023

REFERENCES

- J.P. Ram, H. Manghani, D.S. Pillai, T.S. Babu, M. Miyatake, N. Rajasekar, *Analysis on solar PV emulators: a review*, *Renew. Sustain. Energy Rev.*, **81**, pp. 149–160 (2018).
- N. Kacimi, A. Idir, S. Grouni, M.S. Boucherit, *a new combined method for tracking the global maximum power point of photovoltaic systems*, *Rev. Roum. Sci. Techn. – Électrotechn. et Énerg.*, **67**, 3, pp. 349–354 (2022).
- C.-C. Chen, H.-C. Chang, C.-C. Kuo, C.-C. Lin, *Programmable energy source emulator for photovoltaic panels considering partial shadow effect*, *Energy*, **54**, pp. 174–183 (2013).
- R. Ayop, C. Wei Tan, C. Siang Lim, *The resistance comparison method using integral controller for photovoltaic emulator*, *Int. J. Power Electron. Drive Syst.*, **9**, 2, p. 820 (2018).
- B.C. Babu, S. Gurjar, *A novel simplified two-diode model of photovoltaic (PV) module*, *IEEE J. Photovoltaics*, **4**, 4, pp. 1156–1161 (2014).
- H. Park, Y.-J. Kim, H. Kim, *PV Cell model by single-diode electrical equivalent circuit*, *J. Electr. Eng. Technol.*, **11**, 5, pp. 1323–1331 (2016).
- N. Barth, R. Jovanovic, S. Ahzi, M.A. Khaleel, *PV panel single and double diode models: optimization of the parameters and temperature dependence*, *Sol. Energy Mater. Sol. Cells*, **148**, pp. 87–98 (2016).
- S.M. Hassan Hosseini, A.A. Keymanesh, *Design and construction of photovoltaic simulator based on dual-diode model*, *Sol. Energy*, **137**, pp. 594–60 (2016).
- A.M. Humada, M. Hojabri, S. Mekhilef, H.M. Hamada, *Solar cell parameters extraction based on single and double-diode models: a review*, *Renew. Sustain. Energy Rev.*, **56**, pp. 494–509 (2016).
- I. Moussa, A. Khedher, *Photovoltaic emulator based on PV simulator RT implementation using XSG tools for an FPGA control: Theory and experimentation*, *Int. Trans. Electr. Energy Syst.*, **29**, 8 (2019).
- Y. Mallal, Y. Alidrissi, E.B. Lhoussain, H. Touria, *Design and implementation of a simple and efficient control strategy for PVEs*, *GAZI Univ. J. Sci.*, **34**, 2, pp. 456–475 (2020).
- R. Ayop, C.W. Tan, *Rapid prototyping of photovoltaic emulator using buck converter based on fast convergence resistance feedback method*, *IEEE Trans. Power Electron.*, **34**, 9, pp. 8715–8723 (2019).
- N. Ullah, F. Nisar, A.A. Alahmadi, *Closed loop control of photovoltaic emulator using fractional calculus*, *IEEE Access*, **8**, pp. 28880–28887 (2020).
- D.D.C. Lu, Q.N. Nguyen, *A photovoltaic panel emulator using a buck-boost dc/dc converter and a low-cost micro-controller*, *Sol. Energy*, **86**, 5, pp. 1477–1484 (2012).
- M.A.G. de Brito, L. Galotto, L.P. Sampaio, G. de A. e Melo, C.A. Canesin, *Evaluation of the Main MPPT Techniques for Photovoltaic Applications*, *IEEE Trans. Ind. Electron.*, **60**, 3, pp. 1156–1167 (2013).
- F. Beloucif, A. Boudefel, A. Guerroui, A. Lemzadmi, A. Moussaoui, *Artificial neural network prediction parameters of 10%SF6-90%N2 mixture*, *Rev. Roum. Sci. Techn. – Électrotechn. et Énerg.*, **67**, 2, pp. 139–144 (2022).