International Journal of Power Electronics and Drive System (IJPEDS)
Vol. 16, No. 2, June 2025, pp. 1174~1183
ISSN: 2088-8694, DOI: 10.11591/ijpeds.v16.i2.pp1174-1183

Softplus function trained artificial neural network based maximum power point tracking

Liong Han Wen, Mohd Rezal Mohamed
Electrical, Electronics and Automation Section, Malaysian Spanish Institute, Universiti Kuala Lumpur, Kulim, Malaysia

Article Info

Article history:

Received Aug 15, 2024
Revised Feb 4, 2025
Accepted Mar 1, 2025

Keywords:

Artificial neural network
MPPT
Photovoltaic system
Sigmoid function
Softplus function

ABSTRACT

To optimize the electrical output of a photovoltaic system, maximum power point tracking (MPPT) methods are commonly employed. These techniques work by operating the photovoltaic system at its maximum power point (MPP), which varies based on environmental factors like solar irradiance and ambient temperature, thereby ensuring optimal power transfer between the photovoltaic system and the load. In this paper, an artificial neural network (ANN) is selected as an MPPT technique. The main contribution of the work is to introduce a softplus function trained artificial neural network-based maximum point tracking (SP-ANN MPPT). The proposed method is then compared with a sigmoid function trained artificial neural network-based maximum point tracking (SM-ANN MPPT). The simulation and experimental results show that SP-ANN MPPT is able to track high power than SM-ANN MPPT in different conditions.

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Corresponding Author:

Liong Han Wen
Electrical, Electronics and Automation Section, Malaysian Spanish Institute, Universiti Kuala Lumpur
Kulim Hi-Tech Park, 09000 Kulim, Kedah, Malaysia
Email: liong.han@s.unikl.edu.my

1. INTRODUCTION

The demand for energy is increasing due to the increase in population, industrial, and economic development. Fossil fuel is one of the important sources of energy. However, the storage of fossil fuel in this world is limited, and the usage of fossil fuel is polluting our world. Besides, the inconsistency of fossil fuel prices will affect the economic stability of a country. Therefore, the issue of the development of renewable energy is gaining attention among developed and developing countries. The main sources of renewable energy can be found in the form of solar, hydropower, wind, and bioenergy. Solar energy is more area-independent than other renewable energy resources. Almost everywhere on earth, receiving sunlight can harness solar energy, and it does not pose an environmental threat. Bulky mechanical generators are not required for solar energy harvesting, as with wind, hydro, and vibration energy harvesting systems, and these systems may suffer wear and tear after a long period of time. Therefore, the maintenance costs of parts replacement are relatively high compared to photovoltaic system. Figure 1 illustrates the general block diagram of a photovoltaic system [1]. The input and output of the DC/DC converter is connected to the photovoltaic array and load, respectively. The maximum power point tracking (MPPT) controller generates an appropriate duty cycle for the DC/DC converter so that it can extract maximum power from the photovoltaic (PV) array. The input of the MPPT controller can be the PV array current and voltage [2], [3] or light irradiance intensity and ambient temperature [4], [5].

Partial shading condition (PSC) is one of the common problems in PV systems. PSC occurs when the PV array operates in non-uniform irradiance and temperature situations such as shading from trees, passage of clouds, and internal cell mismatch. The maximum power point (MPP) of a PV system depends on shading patterns on each individual PV module during PSC. Figures 2(a) and 2(b) illustrate the power vs duty cycle curves with different shading patterns for a photovoltaic system in which two PV modules are connected in series. From Figure 2, it is shown that the duty cycle of MPP varies as the shading pattern changes. Hence, maximum power point tracking (MPPT) is a necessary technique in a photovoltaic system to track the MPP. There are different techniques of MPPT [6]–[9]. An artificial neural network (ANN) is used in this work as an MPPT technique. The primary benefits of using the ANN technique with PV systems are its independence from a deep understanding of the internal system characteristics and its ability to identify nonlinear relationships between dependent and independent variables.

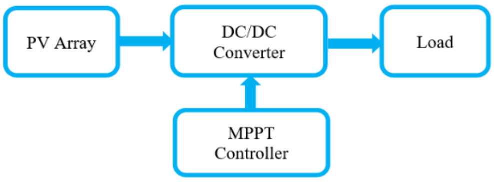
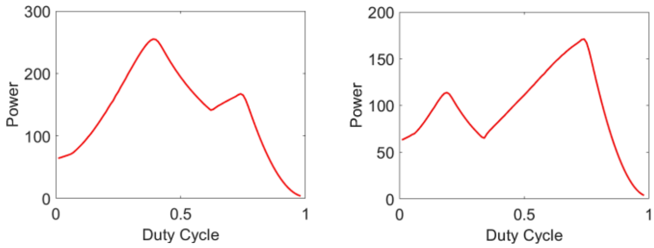


Figure 1. Typical block diagram of a photovoltaic system



(a) (b)

Figure 2. Power vs duty cycle of a PV system for (a) shading pattern A and (b) shading pattern B

2. THEORITICAL ANALYSIS

2.1. Artificial neural network

An artificial neural network (ANN) is an information processing model similar to the human brain [10], [11]. ANN normally starts with the input layer and ends with the output layer. There is/are one or more hidden layers between the input and output layers, showing an ANN with one hidden layer. Figure 3 illustrates an ANN structure with one hidden layer.

The input layer received input data which it is preferable that the range is between zero and one. ANN is composed of a large number of interconnected processing units, which are called neurons, to solve a particular problem. Each neuron is information connected to other neurons by a connection link. Each connection link is associated with weights that contain information about the input signal. This information is utilized by the neural network to address a specific problem. The behavior of an artificial neural network (ANN) is defined by its capability to learn, recall, and generalize training patterns or data, mimicking the functionality of the human brain. Therefore, the processing elements in an artificial neural network (ANN) are referred to as neurons. Each neuron possesses its own internal state, which is known as the neuron's activation level. The activation signal of a neuron is transmitted to other neurons. Figure 4 shows the fundamental structure of a neuron in ANN and the linear relationships between the input and output of a neuron. The activation function is to introduce non-linearity in the network. The output of neurons can be presented as [12], $y = f(z)$, with (1).

$$z = \sum_{m=1}^{M} w_m x_m + b \tag{1}$$

Where y is the output of the neuron, f is the activation function, m is the number of inputs, w_m is the weight corresponding to the incoming input xm, and b is an offset.

2.2. Activation functions

2.2.1. Sigmoid

The sigmoid activation function is a commonly used activation function in neural networks [13]. It maps the input value to a range between 0 and 1. Mathematically, it is expressed as (2) [14].

$$f(x) = \frac{1}{1+e^{-x}} \tag{2}$$

The sigmoid function is characterized by its S-shaped curve, as shown in Figure 5. It takes any real-valued input and squashes it to the (0, 1) range, making it useful for model probabilities or binary classifications.

2.2.2. Hyperbolic tangent

The hyperbolic tangent activation function, commonly known as Tanh, is another popular choice. Tanh is an activation function that is similar to the sigmoid function, but it maps its input to a range between -

1 and 1, providing a wider output range than the sigmoid function, which is 0 to 1. The Tanh activation function is defined as (3) [15].

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{3}$$

Tanh improved upon the limitations of the sigmoid function, mainly by being zero-centered, which helps prevent the vanishing gradient problem to some extent. However, it still suffers from the vanishing gradient issue outside of the range [-1, 1], where the derivative becomes very close to zero, slowing down training for deep networks. Despite being better than the sigmoid function in some cases, Tanh still has some shortcomings that have led to the popularity of the rectified linear unit (ReLU) and its variants. The main drawback of Tanh is that it can exhibit saturated behavior outside the range [-1, 1], leading to slow convergence and gradients approaching zero in those regions. Figure 6 illustrates the Tanh function.

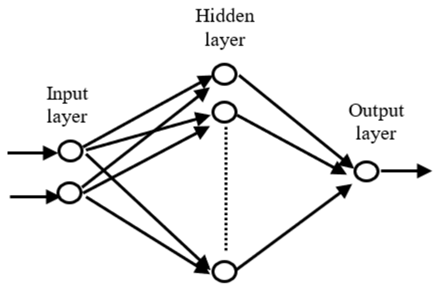


Figure 3. ANN structure

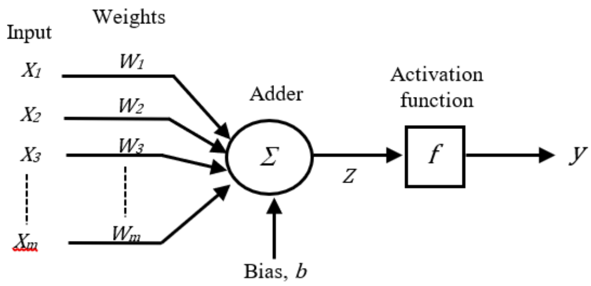


Figure 4. Structure of neuron in ANN

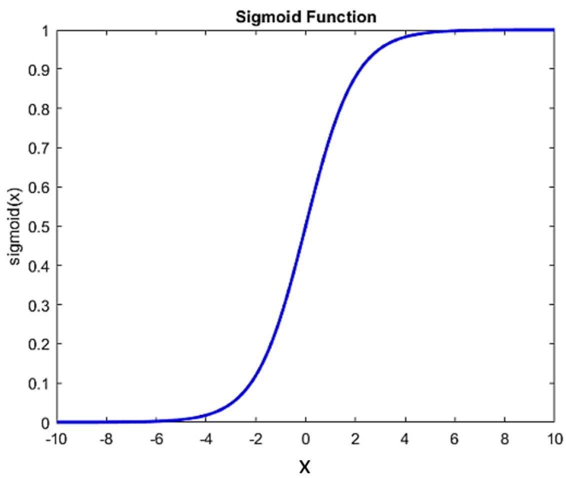


Figure 5. Sigmoid function

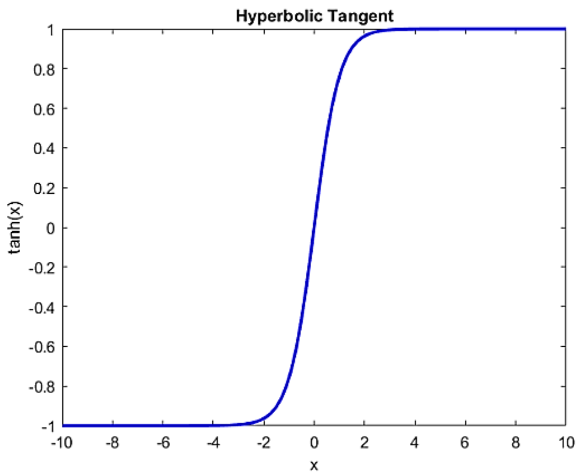


Figure 6. Tanh function

2.2.3. Rectified linear unit

The primary constraints of Sigmoid and Tanh activation functions are their tendency to produce saturated outputs and contribute to heightened complexity. In contrast, the rectified linear unit (ReLU) has emerged as the leading choice for activation functions, due to its simplicity and enhanced performance. It can be written as (4) [16].

$$f(x) = \begin{cases} x & \text{if } x \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

The waveform of the ReLu function is shown in Figure 7.

2.2.4. Softplus

The softplus function serves as a smooth approximation of the ReLU function, effectively eliminating the corner point in the ReLU graph and substituting it with a gentle curve. Softplus presents an alternative to

ReLu due to its differentiability and the ease with which its derivative can be demonstrated. The (5) shows the softplus function formula [17].

$$f(x) = \ln(1 + e^{x}) \tag{5}$$

Figure 8 demonstrates the waveform of the softplus function.

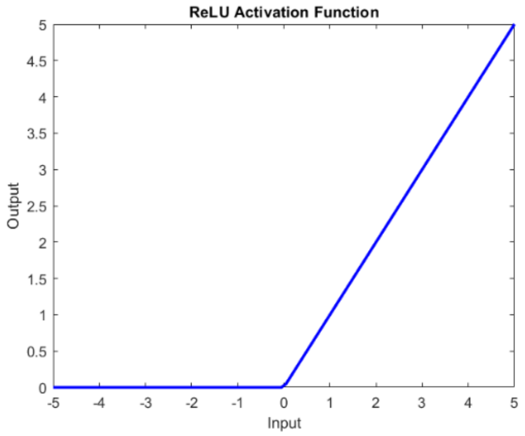


Figure 7. ReLU function

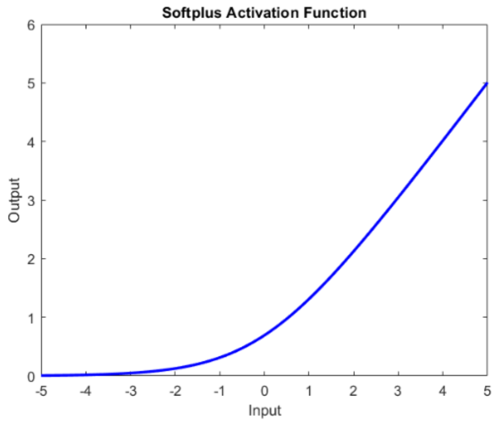


Figure 8. Softplus function

3. MOTIVATION AND METHODOLOGY

From the review of ANN-based MPPT methods [18]–[26], most of the design mechanisms utilize the sigmoid function as the activation function for ANN. However, none of the designs consider the use of the softplus activation function or include hardware validation for ANN-based MPPT. Therefore, the motivation of this paper is to design a softplus function trained ANN-based MPPT (SP-ANN MPPT) using by microcontroller. The proposed method is then compared with a sigmoid function trained ANN-based MPPT (SM-ANN MPPT). Figure 9 demonstrates the proposed block diagram of MPPT. The MPPT controller is developed by practicing ANN. A multi-layer perceptron (MLP) is elected in this paper. The input layers are the irradiance of each PV module and the ambient temperature. The hidden layer contains 150 neurons, which receive data from the input layer and send it to the output layer. The output layer contains a neuron that indicates the duty cycle of the boost converter.

The proposed method is evaluated through both simulation and experimental testing. For the simulation evaluation, a Simulink model is developed, as illustrated in Figure 10. The electrical parameters of the boost converter are set are L = 100 µH, C = 20 µF, and switching frequency (fsw) is 31 kHz. The first step is to collect data for the training of the ANN. To gather a variety of data values, the model is tested under various weather conditions, with irradiance ranging from 500 to 1000 W/m^2 and temperature ranging from 30 °C to 40 °C. The maximum power point (MPP) and the corresponding duty cycle for each weather condition are recorded. The dataset is divided into two groups: training and validation data. The training data is used to train the neural networks, while the validation data is utilized to evaluate the performance of the trained neural networks. In this simulation, the dataset comprises 15 training samples and 5 validation samples. Both the SP-ANN and SM-ANN models are trained using the backpropagation algorithm [27] implemented in MATLAB.

Next, an experimental evaluation was carried out. A main board comprising a boost converter and modules for sensing voltage, current, temperature, and irradiance was designed and fabricated as a single PCB. The electrical parameters of the boost converter are identical to those used in the simulation model shown in Figure 10. An Arduino Mega 2560 was selected as the MPPT controller. Figure 11 illustrates the microcontroller interfacing with the main board via header pins, functioning as an MPPT charge controller. Figures 12(a) and 12(b) illustrate the configuration of a PV module and the overall experimental setup. The photovoltaic modules are shaded with different patterns, and the corresponding photovoltaic modules' irradiances, temperature, and the maximum power duty cycles are recorded to form the dataset for training and validation. The data is sent to the laptop via serial communication. In this experimental evaluation, 100 data is used for training and 30 data is used for validation. The backpropagation algorithm is employed for the training process. After training, the optimized weights and biases were then implemented in an Arduino Mega 2560, which serve as an MPPT controller.

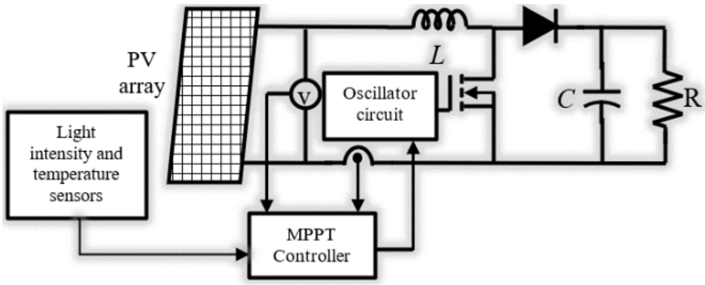


Figure 9. Proposed ANN-based MPPT system

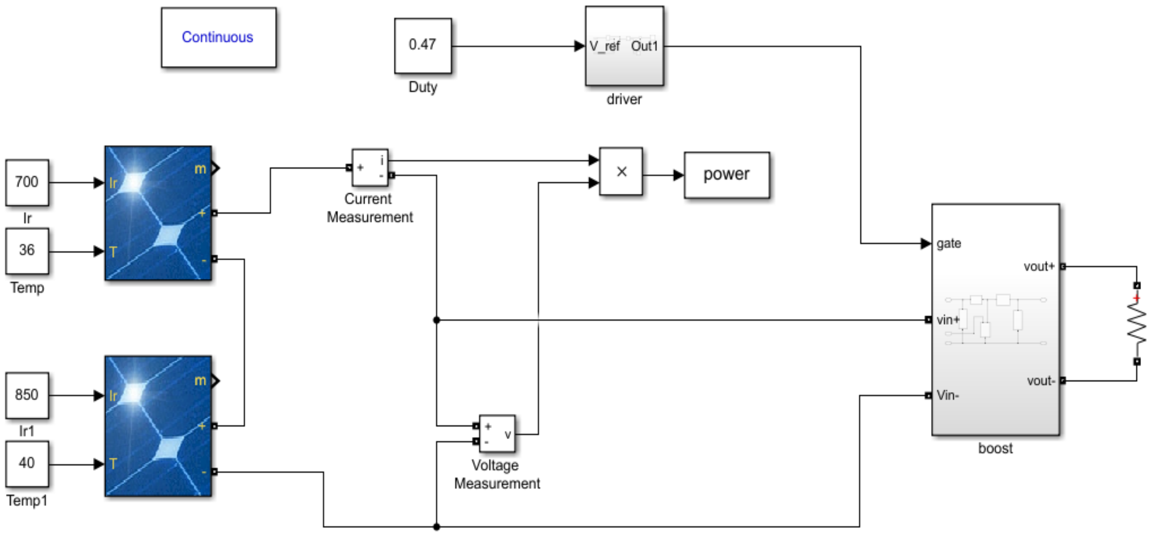


Figure 10. Simulink model for simulation validation

The proposed method is evaluated through both simulation and experimental testing. For the simulation evaluation, a Simulink model is developed, as illustrated in Figure 10. The electrical parameters of the boost converter are set are L = 100 μH, C = 20 μF, and switching frequency (fsw) is 31 kHz. The first step is to collect data for the training of ANN. To gather variety of data values, the model is tested under various weather conditions, with irradiance ranging from 500 to 1000 W/m^2 and temperature ranging from 30 °C to 40 °C. The maximum power point (MPP) and the corresponding duty cycle for each weather condition are recorded. The dataset is divided into two groups: training and validation data. The training data is used to train the neural networks, while the validation data is utilized to evaluate the performance of the trained neural networks. In this simulation, the dataset comprises 15 training samples and 5 validation samples. Both the SP-ANN and SM-ANN models are trained using the backpropagation algorithm [27] implemented in MATLAB.

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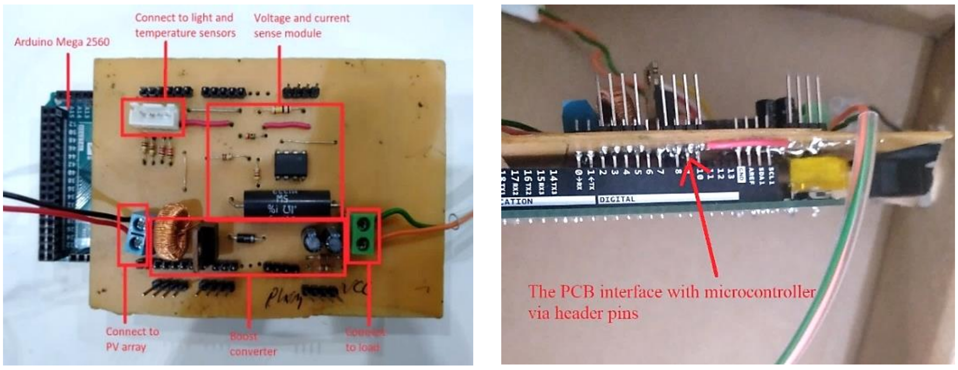


(a) (b)

Figure 11. MPPT charge controller: (a) top view and (b) side view

(a) (b)

Figure 12. Experimental setup for (a) PV module and (b) overall system

4. RESULT AND DISCUSSION

4.1. Simulation results

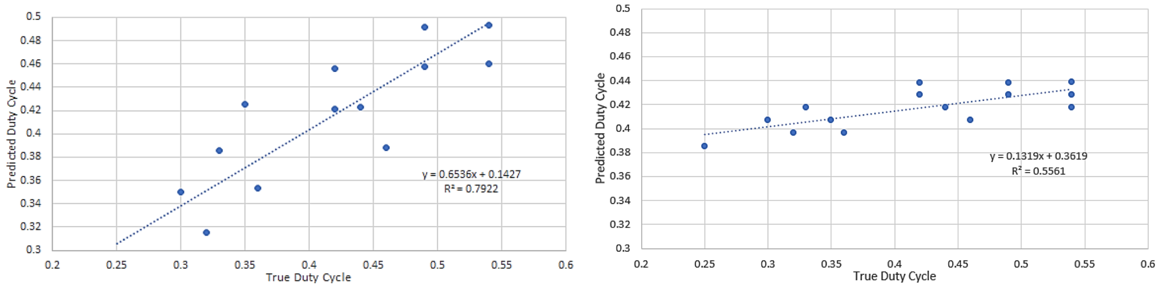
Figures 13 and 14 illustrate the training and validation regression plots for SP-ANN and SM-ANN based on the Simulink model shown in Figure 10. The training regression R-squared values for SP-ANN and SM-ANN are 0.7922 and 0.5561, respectively, while the validation regression R-squared values are 0.9166 and 0.6887, respectively. The simulation results indicate that SP-ANN outperforms SM-ANN. This finding provides motivation to further validate the proposed method experimentally.

4.2. Experimental results

Figure 15 depicts the mean squared error (MSE) plot for both softplus function trained ANN (SP-ANN) and sigmoid function trained ANN (SM-ANN) for the experimental model as shown in Figure 12(b). Both the training and validation curves are decreasing, showing that the neural networks are trained well. The smoothness of the curve in Figure 15(a) is higher than that of Figure 15(b). This indicates that SP-ANN can learn in a stable and consistent manner if compared with SM-ANN. The best performance for both SP-ANN and SM-ANN trainings was achieved at epoch 100000 and 64310, and the MSE observed is 0.00317 and 0.063. Additionally, the difference between the training and validation curves of SP-ANN is smaller than that of SM-ANN. This indicates that SP-ANN can predict the duty cycle more accurately than SM-ANN for both seen and unseen situations.

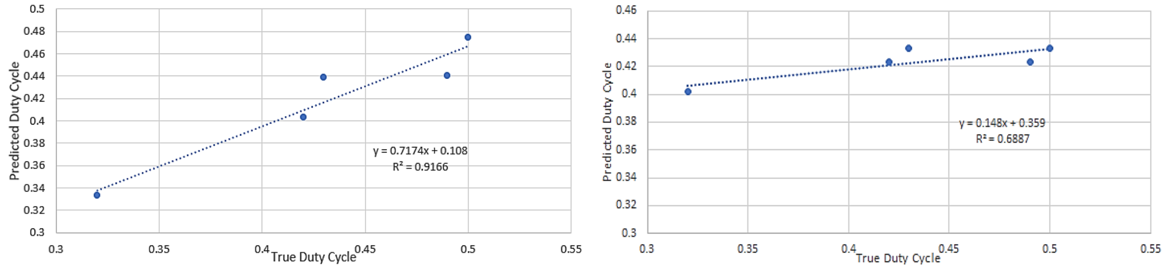
The experimental comparison of SP-ANN and SM-ANN is further validated by using linear regression, as shown in Figures 16 and 17. From the statistical results, it is evident that SM-ANN struggles to accurately predict duty cycles below 0.4. SP-ANN shows an excellent R-squared in both training and validation if compared with SM-ANN. This suggests that SP-ANN can better capture the variability of the overall data than SM-ANN.

In the final step, the performance of SP-ANN and SM-ANN-based MPPT methods was evaluated through field tests conducted outdoors on sunny days. The tests included three validation conditions: unshaded (pattern 1), shaded at PV module 1 (pattern 2), and shaded at PV module 2 (pattern 3), as illustrated in Figure 18. The MPP tracked by both methods were recorded from 7 AM to 7 PM, as shown in Figure 19. The highest power tracked by SP-ANN for patterns 1, 2, and 3 was 4.35 W, 3.8 W, and 3.73 W, respectively. In contrast, the highest power tracked by SM-ANN for the same patterns was 3.88W, 2.77 W, and 2.96 W, respectively. The overall results indicate that the SP-ANN based MPPT is more efficient than the SM-ANN based MPPT.



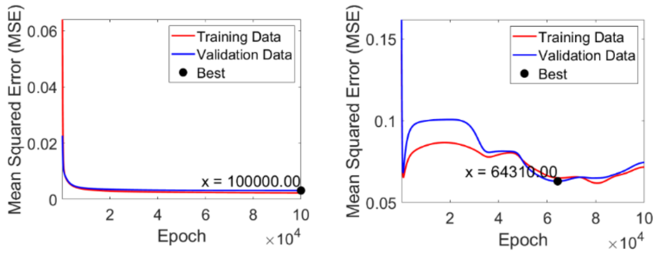
(a) (b)

Figure 13. Training regression plot of (a) SP-ANN and (b) SM-ANN for the simulation model



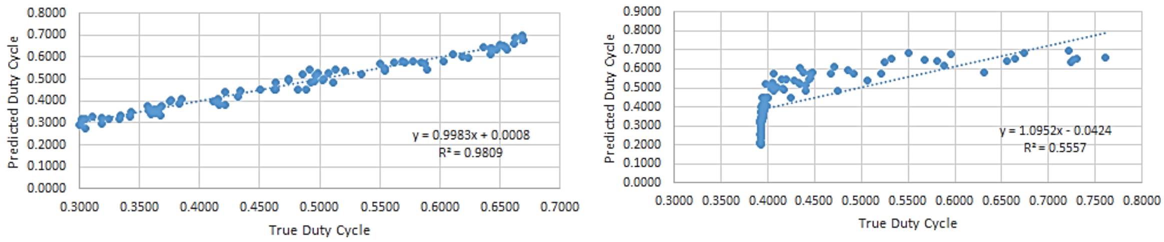
(a) (b)

Figure 14. Validation regression plot of (a) SP-ANN and (b) SM-ANN for the simulation model



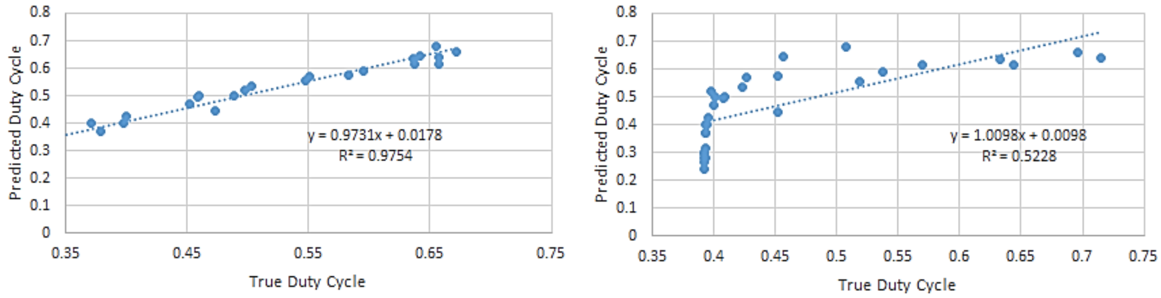
(a) (b)

Figure 15. MSE plot of (a) SP-ANN training and (b) SM-ANN training



(a) (b)

Figure 16. Training regression plot of (a) SP-ANN and (b) SM-ANN for the hardware model

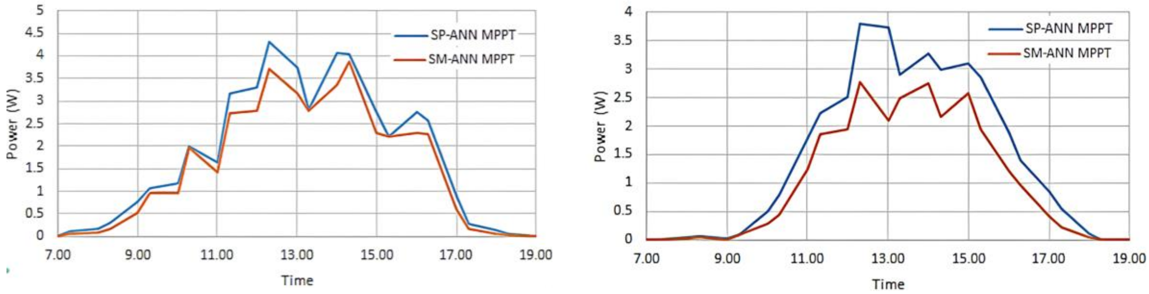


(a) (b)

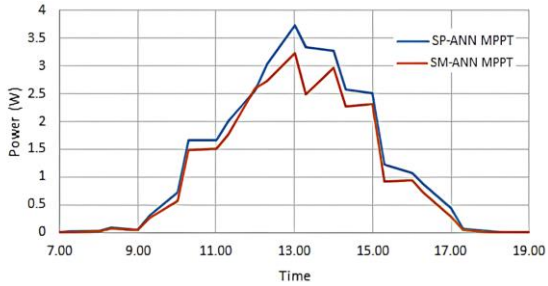
Figure 17. Validation regression plot of (a) SP-ANN and (b) SM-ANN for the hardware model

(a) (b) (c)

Figure 18. Test setup to simulate (a) pattern 1, (b) pattern 2, and (c) pattern 3 shading conditions



(a) (b)



(c)

Figure 19. SP-ANN and SM-ANN based MPPT for (a) pattern 1, (b) pattern 2, and (c) pattern 3

5. CONCLUSION

In this paper, a soft plus function trained ANN-based (SP-ANN) MPPT is proposed. The proposed method is compared with sigmoid function trained ANN-based (SM-ANN) MPPT by using simulation and experimental validation. The proposed photovoltaic system consists of two series connected PV modules, a MPPT controller, boost DC/DC converter, and a resistive load. Arduino Mega 2560 is used as MPPT controller. Based on the performance results, it has been identified that SP-ANN MPPT has better mean square error (MSE) and linear regression if compared with SM-ANN MPPT. Besides, SP-ANN MPPT demonstrates better performance than SM-ANN MPPT in field test. The future work will focus on validate the proposed method with different kinds of load.

ACKNOWLEDGEMENTS

This work was executed with the help of financial and resources available at Electrical, Electronics and Automation Section, Malaysian Spanish Institute, Universiti Kuala Lumpur.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Liong Han Wen	✓		✓	✓	✓	✓		✓	✓	✓			✓	
Mohd Rezal Mohamed		✓		✓		✓	✓		✓	✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data generated and analyzed during the current study are not publicly available due to institutional restrictions but are available from the corresponding author upon reasonable request.

REFERENCES

[1] M. M. A. Awan, M. Y. Javed, A. B. Asghar, and K. Ejsmont, “Performance optimization of a ten check MPPT algorithm for an off-grid solar photovoltaic system,” *Energies*, vol. 15, no. 6, 2022, doi: 10.3390/en15062104.

[2] M. Sarvi and A. Azadian, “A comprehensive review and classified comparison of MPPT algorithms in PV systems,” *Energy Systems*, vol. 13, no. 2, pp. 281–320, 2022, doi: 10.1007/s12667-021-00427-x.

[3] G. A. Raiker, U. Loganathan, and S. B. Reddy, “Current control of boost converter for PV interface with momentum-based perturb and observe MPPT,” *IEEE Transactions on Industry Applications*, vol. 57, no. 4, pp. 4071–4079, 2021, doi: 10.1109/TIA.2021.3081519.

[4] C. Gonzalez-Castano, C. Restrepo, S. Kouro, and J. Rodriguez, “MPPT algorithm based on artificial bee colony for PV System,” *IEEE Access*, vol. 9, pp. 43121–43133, 2021, doi: 10.1109/ACCESS.2021.3066281.

[5] M. N. I. Jamaludin *et al.*, “An effective salp swarm based MPPT for photovoltaic systems under dynamic and partial shading conditions,” *IEEE Access*, vol. 9, pp. 34570–34589, 2021, doi: 10.1109/ACCESS.2021.3060431.

[6] M. F. Jalil, S. Khatoon, I. Nasiruddin, and R. C. Bansal, “Review of PV array modelling, configuration and MPPT techniques,” *International Journal of Modelling and Simulation*, vol. 42, no. 4, pp. 533–550, 2022, doi: 10.1080/02286203.2021.1938810.

[7] H. Abidi, L. Sidhom, and I. Chihi, “Systematic literature review and benchmarking for photovoltaic MPPT Techniques,” *Energies*, vol. 16, no. 8, 2023, doi: 10.3390/en16083509.

[8] E. S. Wirateruna and A. F. A. Millenia, “Design of MPPT PV using Particle swarm optimization algorithm under partial shading condition,” *International Journal of Artificial Intelligence & Robotics (IJAIR)*, vol. 4, no. 1, pp. 24–30, 2022, doi: 10.25139/ijair.v4i1.4327.

[9] M. Fathi and J. A. Parian, “Intelligent MPPT for photovoltaic panels using a novel fuzzy logic and artificial neural networks based on evolutionary algorithms,” *Energy Reports*, vol. 7, pp. 1338–1348, 2021, doi: 10.1016/j.egyr.2021.02.051.

[10] M. F. El-Khatib and E. A. Aner, “Efficient MPPT control for a photovoltaic system using artificial neural networks,” *ERU Research Journal*, vol. 2, no. 3, pp. 385–398, May 2023, doi: 10.21608/erurj.2023.301364.

[11] M. T. Hussain, A. Sarwar, M. Tariq, S. Urooj, A. BaQais, and M. A. Hossain, “An evaluation of ANN algorithm performance for MPPT energy harvesting in solar PV Systems,” *Sustainability*, vol. 15, no. 14, p. 11144, Jul. 2023, doi: 10.3390/su151411144.

[12] O. I. Abiodun *et al.*, “Comprehensive review of artificial neural network applications to pattern recognition,” *IEEE Access*, vol. 7, pp. 158820–158846, 2019, doi: 10.1109/ACCESS.2019.2945545.

[13] T. Szandała, “Review and comparison of commonly used activation functions for deep neural networks,” *Studies in Computational Intelligence*, vol. 903, pp. 203–224, 2021, doi: 10.1007/978-981-15-5495-7_11.

[14] Y. Koçak and G. Üstündağ Şiray, “New activation functions for single layer feedforward neural network,” *Expert Systems with Applications*, vol. 164, p. 113977, Feb. 2021, doi: 10.1016/j.eswa.2020.113977.

[15] K. Et-Torabi and A. Mesbahi, “MPPT based artificial neural network versus pertub & observe for photovoltaic energy conversion system,” *E3S Web of Conferences*, vol. 336, 2022, doi: 10.1051/e3sconf/202233600044.

[16] I. Jahan, M. F. Ahmed, M. O. Ali, and Y. M. Jang, “Self-gated rectified linear unit for performance improvement of deep neural networks,” *ICT Express*, vol. 9, no. 3, pp. 320–325, 2023, doi: 10.1016/j.icte.2021.12.012.
[17] X. Liao, T. Zhou, L. Zhang, X. Hu, and Y. Peng, “A method for calculating the derivative of activation functions based on piecewise linear approximation,” *Electronics (Switzerland)*, vol. 12, no. 2, 2023, doi: 10.3390/electronics12020267.
[18] F. Saeed, M. H. Yousuf, H. A. Tauqeer, M. R. Akhtar, Z. A. Abbas, and M. H. Khan, “Performance benchmark of multi-layer neural network based solar MPPT for PV applications,” in *2021 International Conference on Emerging Power Technologies, ICEPT 2021*, 2021. doi: 10.1109/ICEPT51706.2021.9435583.
[19] A. G. Abdullah, M. S. Aziz, and B. A. Hamad, “Comparison between neural network and P&O method in optimizing MPPT control for photovoltaic cell,” *International Journal of Electrical and Computer Engineering*, vol. 10, no. 5, pp. 5083–5092, 2020, doi: 10.11591/IJECE.V10I5.PP5083-5092.
[20] M. N. Ali, K. Mahmoud, M. Lehtonen, and M. M. F. Darwish, “Promising mppt methods combining metaheuristic, fuzzy-logic and ann techniques for grid-connected photovoltaic,” *Sensors (Switzerland)*, vol. 21, no. 4, pp. 1–18, 2021, doi: 10.3390/s21041244.
[21] S. A. Rizzo, N. Salerno, G. Scelba, and A. Sciacca, “Enhanced hybrid global MPPT algorithm for PV systems operating under fast-changing partial shading conditions,” *International Journal of Renewable Energy Research*, vol. 8, no. 1, pp. 221–229, 2018, doi: 10.20508/ijrer.v8i1.6704.g7295.
[22] Y. E. A. Idrissi, K. Assalaou, L. Elmahni, and E. Aitiaz, “New improved MPPT based on artificial neural network and PI controller for photovoltaic applications,” *International Journal of Power Electronics and Drive Systems*, vol. 13, no. 3, pp. 1791–1801, 2022, doi: 10.11591/ijpeds.v13.i3.pp1791-1801.
[23] S. R. Kiran, C. H. H. Basha, V. P. Singh, C. Dhanamjayulu, B. R. Prusty, and B. Khan, “Reduced Simulative performance analysis of variable step size ANN based MPPT techniques for partially shaded solar PV Systems,” *IEEE Access*, vol. 10, pp. 48875–48889, 2022, doi: 10.1109/ACCESS.2022.3172322.
[24] R. Divyasharon and R. Narmatha Banu, “Performance assessment of Boost, Cuk and Zeta converter with neural network MPPT in PV systems for varying weather patterns,” *International Journal of Engineering Research and Applications*, vol. 12, no. 4, pp. 9–20, 2022.
[25] K. Krishnaram, T. S. Padmanabhan, F. Alsaif, and S. Senthilkumar, “Performance optimization of interleaved boost converter with ANN supported adaptable stepped-scaled P&O based MPPT for solar powered applications,” *Scientific Reports*, vol. 14, no. 1, 2024, doi: 10.1038/s41598-024-58852-8.
[26] M. Yılmaz and M. Corapsiz, “PSO training neural network MPPT with CUK converter topology for stand-alone PV systems under varying load and climatic conditions,” *Türk Doğa ve Fen Dergisi*, vol. 13, no. 1, pp. 88–97, 2024, doi: 10.46810/tdfd.1423852.
[27] A. Singh, S. Kushwaha, M. Alarfaj, and M. Singh, “Comprehensive overview of backpropagation algorithm for digital image denoising,” *Electronics (Switzerland)*, vol. 11, no. 10, 2022, doi: 10.3390/electronics11101590.

BIOGRAPHIES OF AUTHORS

Liong Han Wen received a B.Eng. (Hons) degree in Electronics and Control System Engineering from Liverpool John Moores University in 2005 and an M.Sc. degree in Electrical and Electronic from the University of Bradford in 2013. He is currently working toward a Ph.D. degree in Electrical and Electronic Engineering at Universiti Kuala Lumpur. He can be contacted at email: lionghanwen@gmail.com.

Mohd Rezal Mohamed is a senior lecturer in Electrical, Electronics and Automation Section at the Malaysian Spanish Institute, Universiti Kuala Lumpur, Kulim, Kedah, Malaysia. He received his B.Eng., M.Sc., and Ph.D. degrees in Electrical and Electronics Engineering from Universiti Putra Malaysia and Universiti Sains Malaysia in 2002, 2008, and 2019, respectively. His research interests include the field of electric machines, optimization, electromagnetic applications, electric vehicles, power electronics, and motor drives. He can be contacted at email: mrezal@unikl.edu.my.