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# Artificial intelligent controller-based energy management system for grid integration of PV and energy storage devices

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**ABSTRACT**

In the modern world, photovoltaic (PV) energy generation is becoming more prevalent and cost-effective. To address climate change, many countries have prioritised photovoltaics and made significant investments in energy generation. Because of its non-linear nature, solar energy generation is extremely difficult. This is completely dependent on the solar radiation and the outside temperature. The maximum power generation of a PV system in non-linear weather circumstances and the grid integration of PV with power management are discussed in this article. Artificial intelligence (AI) is vital for improving the energy output of PV systems across a wide range of environmental conditions because traditional controllers do not aid a solar system in producing the maximum energy. The grid integration of PV and energy management systems (EMS) was covered in the later part of this article. In this paper, artificial intelligence is used to provide customers with continuous power through a battery system, which plays a critical role in energy management. Furthermore, the suggested model was simulated in MATLAB and its performance was evaluated under various operational scenarios. To demonstrate the effectiveness of the proposed system, the results are compared to IEEE 519.



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## 1. INTRODUCTION

As energy consumption carbon dioxide emissions and global insufficiency of demand and supply rise, so does population growth and urbanisation. Due to environmental concerns, energy scarcity, and pollution, wind and pv power are the most prominent alternative sources that are presently the dominant energy source for present power system [1], [2]. An microgrid (MG) is a less voltage supply system with controlled reserves and consumers that incorporates variable distributed renewable sources such as wind, photovoltaic (PV), and fuel cells [3]–[5]. Improve network stability while providing reliability, high quality power. Due to the low penetration of renewable energy (RG) generation, controlling an MG with a wide combination of distributed generators (DGs), cyclic loads, and energy storage aggregator (ESA) is even more challenging [6].

Maximum power point tracking (MPPT) methods are widely utilized to regulate the RG [7]-[8]. As a result of the uncontrolled climate conditions, it is considered as a non-regulable generation. The MG concept of integrating non-conventional energy sources with battery storage systems (BSS) has received a lot of interest and admiration [9], [10]. The stability of the system facilitates renewable energy integration by supporting the whole power system by storing energy at a reduced cost during off-peak hours. The microgrid system's stability and operational performance are dependent on efficient energy management [11], [12]. Because of the complexity of the power system, effective power flow control between generation and demand is reliant on the entire power grid's dynamic behaviour [13].

Mbungu *et al*. [14] presented the evolution of micro grid was discussed in terms of distribution management, smart energy coordination and communication technology. Reddy and Ramasamy [15] presented adaptive-neuro-fuzzy inference system (ANFIS) based MPPT and developed a sepic topology for DC-DC conversion. Almazrouei *et al*. [16] proposed a predictive energy managemnent technique with forecasting and battery storage, which helps power flow controls in the grid.

The gaps identified in previous research are given in Table 1, and these are addressed by the proposed method. The advantages of this method are: i) It has the ability to deal with non-linear models; ii) It is dynamic and able to work online with real-time systems; iii) Yields high MPPT photovoltaics (PV) output power; and iv) Efficient energy management system. Due to these benefits, we are interested in developing an artificial intelligence (AI) controller-based energy management system (EMS) for grid integration of PV and energy storage devices.

The rest of this work is split into the following sctions. Section 2, presents the simulation results of ANFIS algorithm developed for MPPT and grid integration of a 100 kW photovoltaic system with battery storage system with an energy management structure. Section 3 implements the multilayer feedforward neural network (MFNN) method to describe the grid integration of a 100 kW photovoltaic system with a battery system and an energy management framework. The suggested system's simulated results are discussed in section 4, and the conclusion is stated in section 5.

Table 1. Literature review on grid integration of PVand battery energy management system (BEMS)

| Ref. No | Summary | Gap identified |
|---|---|---|
| [17] | "This paper presents the development of an intelligent dynamic energy management system for smart (IDEMS) microgrid operations. They Developed optimal control strategies and approximate cost-to-go functions using adaptive dynamic programming and reinforcement learning." | The battery management system's dynamic state prediction has not been detected. |
| [18] | "For preserving the supply-demand balance in a grid, this study provides an optimal control-based power management of numerous batteries. It takes into account the implications of time-of-use pricing, time-varying distributed generation and loads, charging and discharging of batteries." | Real-time communication with one or more local controllers has failed. Collaboration and distributed control techniques need to be mproved. |
| [19] | "This paper discussed the energy management strategies in interconnected multi microgrids (MMG). It uses mixed integer linear programming optimization tool for EMS." | BESS efficiency and coordination control of MMG requires improvements in batterySoC/SoD |
| [20] | "For energy management and an electric vehicle charging stations (EVCS) with regulated charging capabilities, discussed the implementation of a deep learning-based forecasting method. The EMS's goal was to reduce the amount of power imported from the main power grid." | Forecasting results are less accurate and needs to be improved. |
| [21] | "This article presents the development of an intelligent technique of adaptive-neuro-fuzzy inference system (ANFIS) based on Maximum Power Point Tracking algorithm with PI controller in order to increase the performance of the photovoltaic panel." | Presented the MPPT tracking techniques but requires deep analysis on MPPT PV output power. |
| [22] | "In this paper, a grid connected PV based electric vehicle charging station with the use of BES is proposed." | The proposed p&o optimization is slow and less efficient than ANFIS. |
| [23] | "Presented linear regression interaction (LIR) technique with ANFIS to extract maximum power from PV systems." | Analysis is required on MPPT results and EMS. |
| [24] | "This paper proposes a buck-boost converter-based standalone PVsystem for power generation with maximum power point tracking and an ANFIS-controlled converter." | This model was designed for a 200w stand-alone PV system and will need to be improved to work in the KW range. |

## 2. ANFIS BASED PV MPPT

It is challenging to achieve maximum output from a PV power system because of its non-linear nature. The production of electricity by a PV system is completely rely on the motion of the sun's radiation. Maximizing PV system power under varied operating conditions was achieved by using the ANFIS. It is depicted in Figure 1 using the parameters in Table 2 for a 100 kW PV system. In this model, the 100 kW PV system is connected to a power converter and controlled by the ANFIS MPPT algorithm. Using PV voltage and PV current, the ANFIS method was taught to calculate the duty cycle of a semiconductor switch.

Figure 2 illustrates the PV system's ANFIS MPPT, training data and inference rules. The ANFIS algorithm's structure is depicted in Figure 2(a), as shown. Approximately 3000 data points were used to train, test, and verify this approach. Figure 2(b) illustrates the MATLAB simulation model generates training data and saves it in the workspace. Using training, testing, and validation, the ANFIS network generates two inputs and one output membership function (triangular) based on these variables. A semiconductor switch's duty cycle ranges from 0.4 to 1. The fuzzy rule-based system depicted in Figure 2(c) is shown. The output voltage, current, and power of the 100 kW PV system were evaluated before running the ANFIS algorithm.

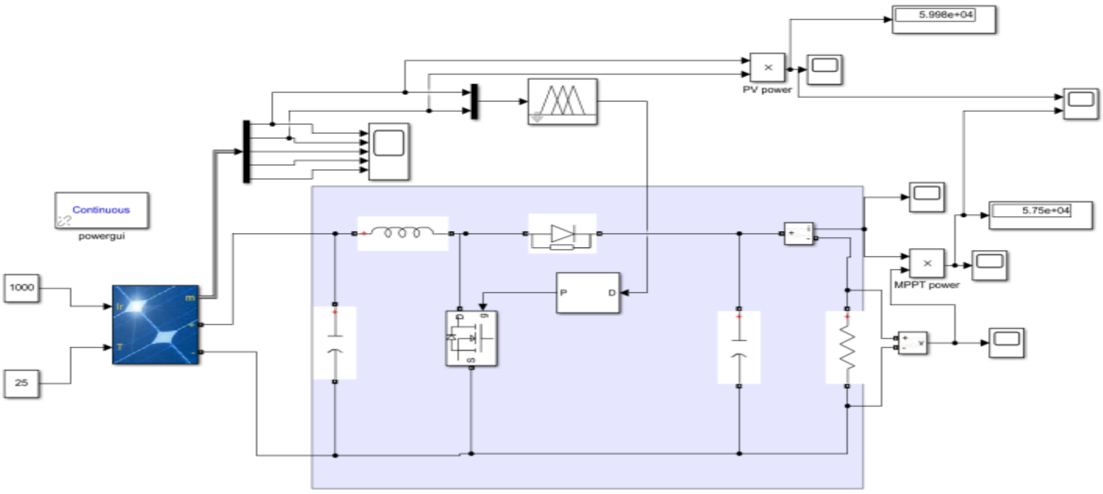
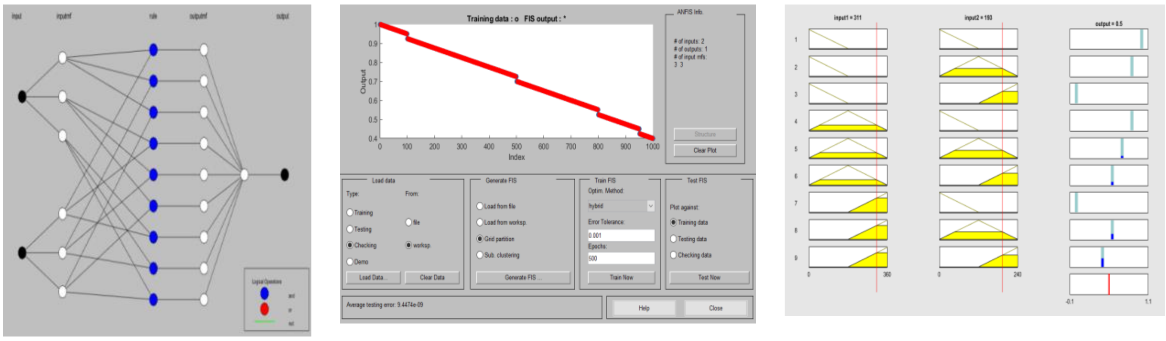



Figure 1. ANFIS maximum power point tracking of 100 kW PV simulation model

Table 2. Battery parameters

| Sl. No | Battery specifications | |
|---|---|---|
| 1 | Type of battery | Lithium-Ion (Li-ion) |
| 2 | Volt rating | 48 V |
| 3 | Ampere hour rating | 300 Ah |
| 4 | Initial SoC | 75 % |
| 5 | V-Cut off | 36 V |
| 6 | Fully charged voltage | 55.8 V |



(a) (b) (c)

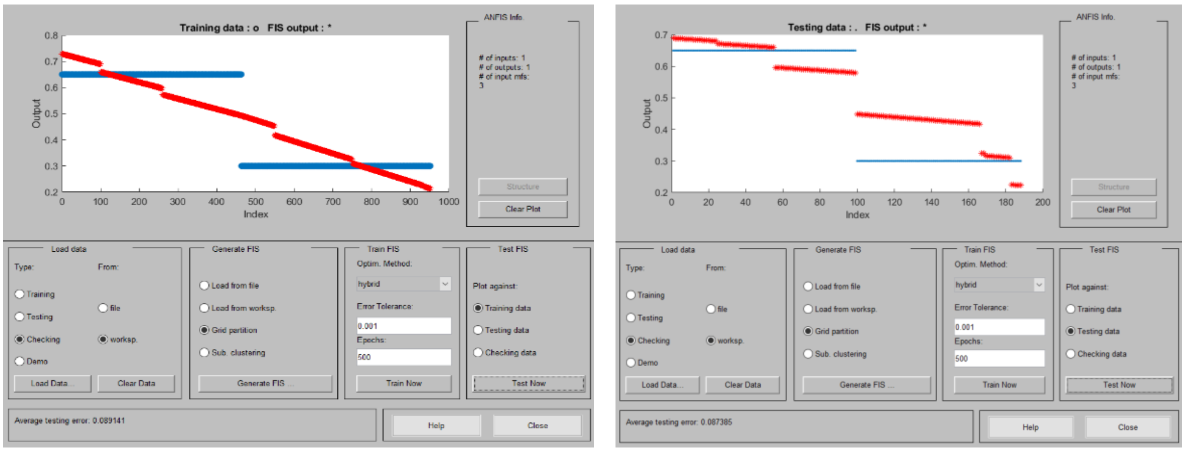
Figure 2. PV system's ANFIS (a) MPPT, (b) training data, and (c) inference rules

### 2.1. ANFIS based grid integration of PV and battery management system

As depicted in Figure 1, a three-phase distribution line of 400 V and 50 Hz was employed in the grid integration of a 100kW photovoltaic simulation model. The 100 kW MPPT controller can be connected to the ANFIS algorithm via a 3-phase inverter. A voltage source converter (VSC) was utilised to regulate the three-phase converter that was linked to the grid. This VSC controller consists of a phase lock loop, a voltage regulator, and a current regulator. With the help of this controller, the inverter linked to the network can match the frequency and voltage of the network, facilitating photovoltaic model that are synced with the power grid. The VSC monitor collects data on three-phase voltage and grid current on a regular basis and feeds it into a phase interlock loop that locks the frequency. A voltage regulator is required to maintain the inverter's voltage stable when it is linked to the three-phase network and synchronised with the distribution network. The current controller regulates the natural and reactive power flows in the 3-phase inverter. The controller regulates currents in the three-phase inverter's direct axis Id and quadrant axis Iq. Finally, phase width modulation is used to produce the switching pulses of the grid-connected 3-ph inverter. In this article, a bidirectional DC-DC converter (BDC) is used to transfer electricity from solar (PV) to battery and from battery to load.

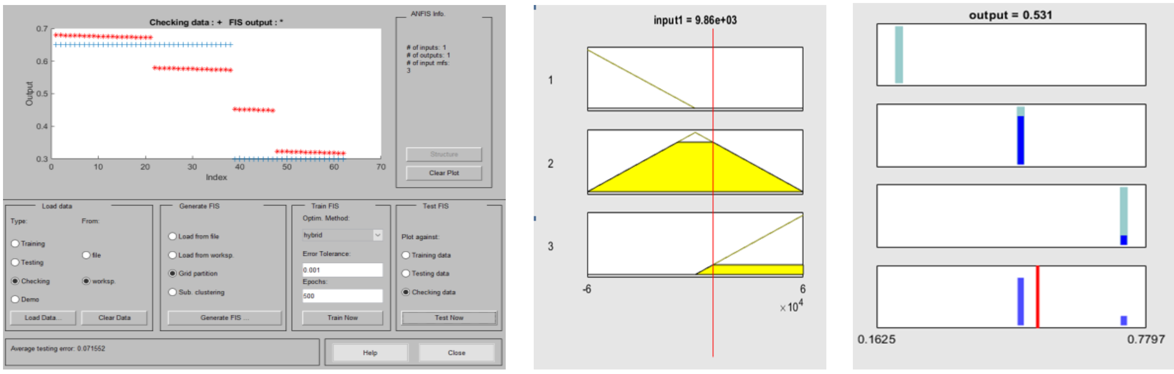
In MATLAB, nearly 2400 data points were used to construct the ANFIS battery management system (train, test, and validate). Both inputs and outputs (the difference between solar output power and customer demand) (changing pulse of BDC for battery state of charge (SoC) and state of discharge (SoD)) are included in the training. A simulation model is used to observe and analyse these data under various operating conditions (viz. Changing solar power & changing load). The ANFIS battery management system (BMS) as shown in Figure 3 was put to the test with an average of 0.089141. The average test error for ANFIS' battery management and system is 0.087385, as shown in Figure 3(a) and Figure 3(b).

Figure 4 illustrates the ANFIS validation data and ANFIS rules for BEMS. For the ANFIS BMS, a test error of 0.071552 is shown in Figure 4(a). The ANFIS network produced an inevitably formed membership function of input and output, which was then cross-pending, rules-based battery management, as illustrated in Figure 4(b). BMS ANFIS rules are; i) If (input1=in1mf1), so (output=out1mf1) (1), ii) If (input1=in1mf2), so (output=out1mf2) (1), and iii) If (input1=in1mf3), so (output=out1mf3) (1).




(a) (b)

Figure 3. ANFIS-BEMS’s (a) training data and (b) test data




(a) (b)

Figure 4. ANFIS (a) validation data and (b) rules for BEMS

System performance was examined in various operating conditions on a 100kW PV system linked with this battery management system. Figure 5 depicts the battery SoC and SoD with respect to Photovoltaic energy higher than load (battery under SoC) and lower than load (battery under SoD). First, if the solar PV produced 100 kW of power that is larger than the load power, then this is the first situation that can occur. These pulse width modulation (PWM) pulses for a bidirectional converter were generated by the controller for the battery and it’s SoC. Under the second condition, PV generates more than 60 kW of power, which is higher than 63 kW. The controller, generated PWM pulses for a bidirectional converter for the battery and its SoD. Changes in PV power generation can be accommodated by the proposed model. A constant 25 kW demand is combined with photovoltaic power generation of 25 kW from 0 to 1 second, 50 kW from 1 second to 2 seconds, and 75 kW from 2 seconds to 3 seconds. If the PV system generates less power than the demand, the battery begins to degrade in 0 to 1 second (assuming a 75 percent starting battery capacity). The battery starts charging when the PV generates 50 kW for 1 to 2 seconds and 75 kW for 2 to 3 seconds, as shown in Figure 6. Figure 7 shows the load voltage and current waveforms, as well as the distribution grid. The standard consumer load's grid current and voltage are 15 Amps and 380 volts. Furthermore, as seen Figure 8, the coordinated utility grid power quality was investigated utilising total harmonic distortion (THD) for the voltage and current profiles (given as 3.45% and 1.73% respectively).

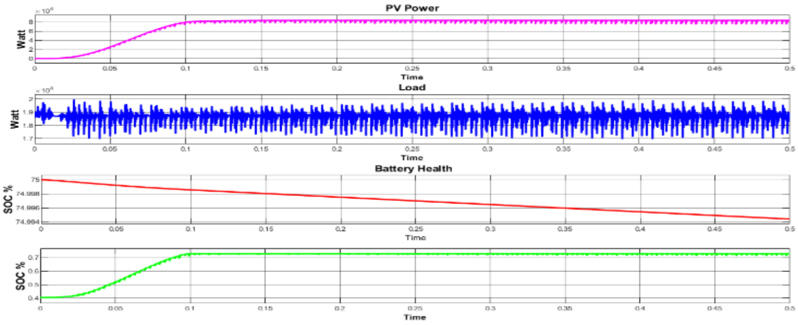



Figure 5. Photovoltaic energy at higher than load (battery under SoC) and lower than load (battery under SoD)

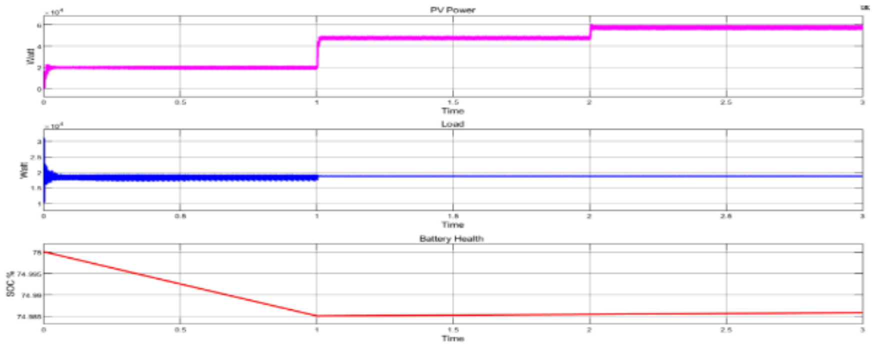



Figure 6. SoC of battery at variable PV power and constant load

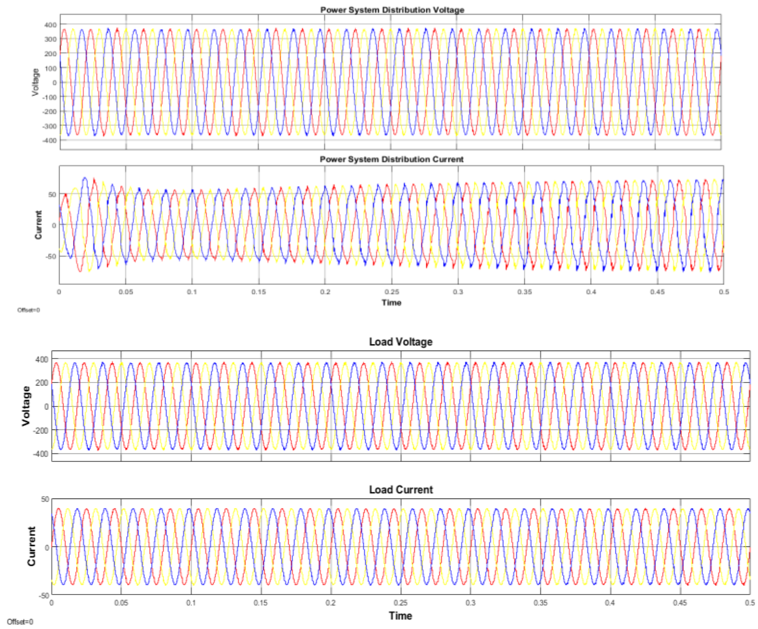



Figure 7. Distribution grid V and I & $V_L$ and $I_L$ waveforms

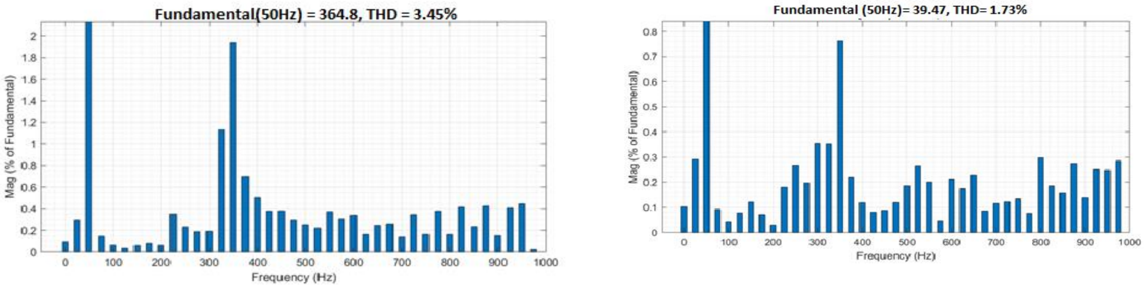
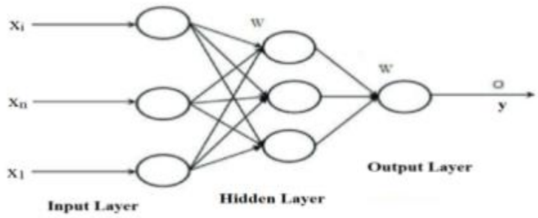


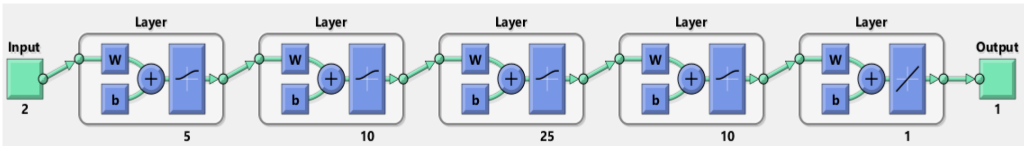

Figure 8. THD of $V_{Load}$ and I $_{Load}$

## 3. MULTILAYER FEEDFORWARD NEURAL NETWORKS BASED SOLAR (PV) MPPT ALGORITHM

An artificial neural network (ANN) is a type of artificial intelligence that consists of a collection of interlinked basic units called neurons. Essentially, each neuron represents a mapping, particularly one with several inputs and only one output. The neuron's output is a function of the neuron's inputs as a whole. Neurons utilise activation functions in the output of their neuronal outputs. The sign for a single neuron displays the number of arrows emanating from the neuron's sole output, which can be applied to other neurons. Perceptron is a term for a network design that simply includes the input and output layers. There is no intermediary layer between the input and output layers in a perceptron. Input and output have a linear relationship. The weighted sums of signals delivered from the input to the output indicate the direct interaction between the two levels. Multi-layer perceptrons (MLP) are neural networks that have many layers between input and output. Feedforward neural network (FFNN) are another name for MLP networks in neural network modelling (NNM). FFNN's network has a "hidden layer," which serves as an additional layer of the network. The hidden layer receives the weighted signal from the input layer. The buried layer neurons receive the signals from the inputs. The underlying layer has an activation function that processes signals that enter the buried neurons. Because hidden layer activation functions are nonlinear, they can be employed as transfer functions. The output layer receives the weighted total of the hidden layer's neuron outputs. On its path to the output layer, the activation function across this layer processes the incoming signal. Figure 9 depicts the architecture of MLP neural network and proposed MFNN-MPPT system.




(a)




(b)

Figure 9. Architecture of (a) MLP network and (b) Proposed MFNN for Photovoltaic MPPT system

As seen in Figure 9(a) and (b), the MLP has n inputs xi, I = 1,..., n, and a output neuron y, & k neurons in the hidden layer [25]. The function zj represents the output of a buried layer neuron, where j=1, ..., k. The input x1, ..., xn is uniformly distributed among the neurons in the hidden layer. In the input layer, identity mapping is the neuron's activation function. In the hidden and output layers of the brain, neuron activation functions are expressed using fh and fo, respectively. The activation features of each individual signal processing element are determined by a function of R to R. The architecture's math formula can be expressed as (1).

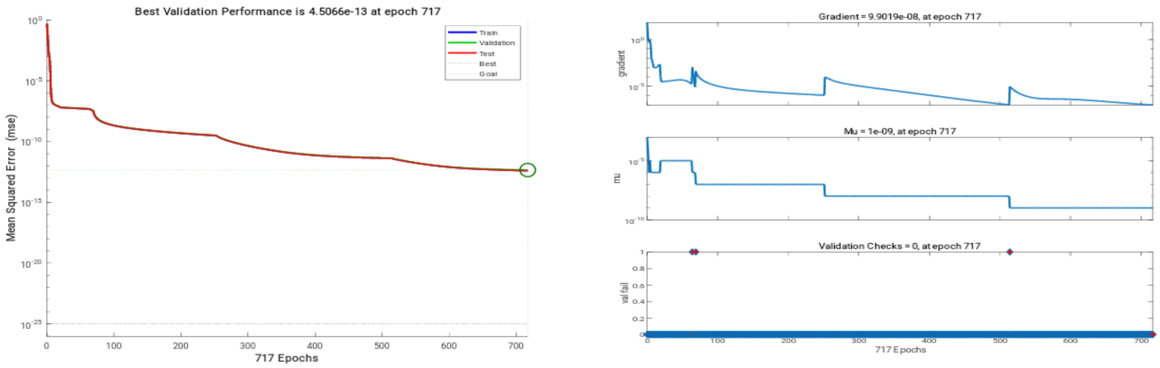
$$Y = f^{o}\left(\sum_{J=1}^{k} W_j^{o} f_j^{h}\left(\Sigma_{i=1}^{n} W_{ji}^{h} X_i\right)\right) \quad (1)$$

Where $f^0$ is the output layer activation function and $f_j^h$ is the hidden layer activation function, and if a bias is introduced to the input layer and the activation function of each neuron in the hidden layer is $f^h$the preceding equation becomes (2).

$$Y = f^{o}\left(W^{b} + \sum_{J=1}^{k} W_j^{o} f_j^{h}\left(\Sigma_{i=1}^{n} W_{ji}^{h} X_i\right)\right) \quad (2)$$

It has been recommended that a feed forward neural network (FFNN) model be constructed for an algorithm to find the maximum power spots for the Photovoltaic system. When it comes to power, this network is equipped with both PV voltage and PV current. The production capacity of this network is determined by the duty cycle of the DC-DC converter. There are five hidden layers between the contribution layer and the production layer. As shown in fig 9b, each hidden layer employs a separate number of neurons, with 5 neurons in layer 1, 10 neurons in layer 2, 25 neurons in layer 3, 10 neurons in layer 4, and 1 neuron in layer 5. More than 15 thousand pieces of data, including PV voltage, current, and duty cycle, have been used to train the proposed network.

Figure 10 illustrates the proposed MFNN validation performance and solar mppt's gradient, mean and validation results. The MPPT algorithm was generated using more than 1000 epochs of training data. As be shown in Figure 10(a), the proposed MNFF has the best driving performance of 4.5066e-13 and Figure 10(b) shows the suggested MNFF's gradient analysis, Mu, and validation check. In the end, Figure 11 shows the predicted network regression value.




(a) (b)

Figure 10. Proposed MFNN (a) Best validation performance and (b) Solar mppt's gradient, mean and validation

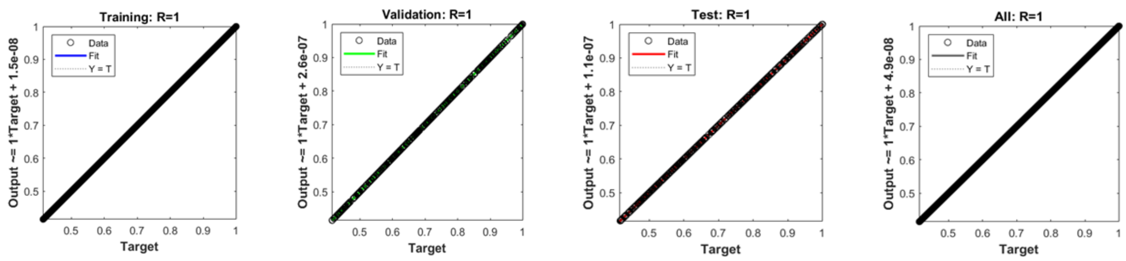



Figure 11. Proposed MPPT algorithm training, validation analysis, test and overall performance

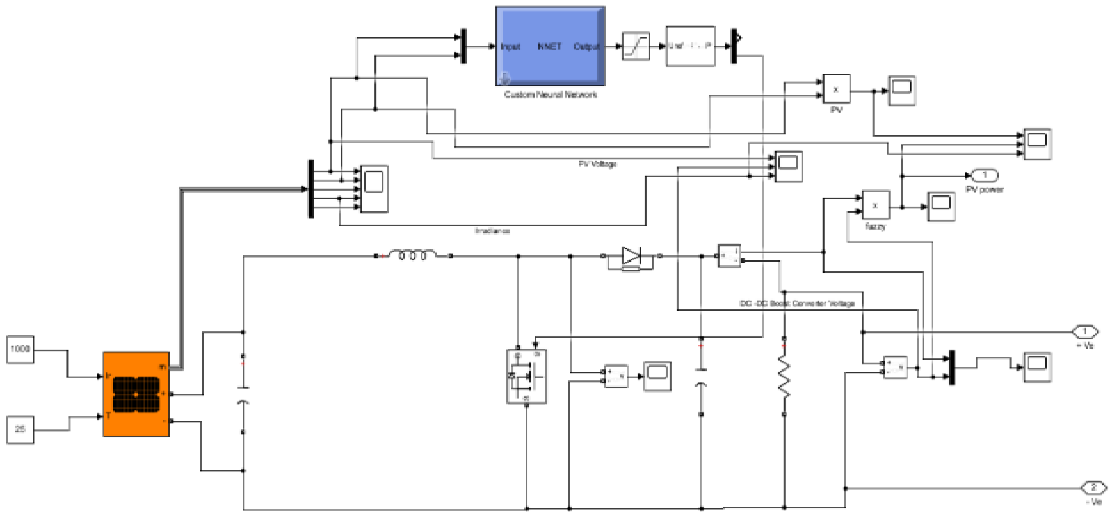
## 4. RESULTS

The MFNN-based PV MPPT algorithm that was suggested and built has been implemented to a 100-kW Photovoltaic power system and its performance at various irradiances illustrated in Figure 12. Simulation model of the proposed MFNN-based MPPT system shown in Figure 12(a) and Figure 12(b) depicts how the system performs at various irradiation levels.

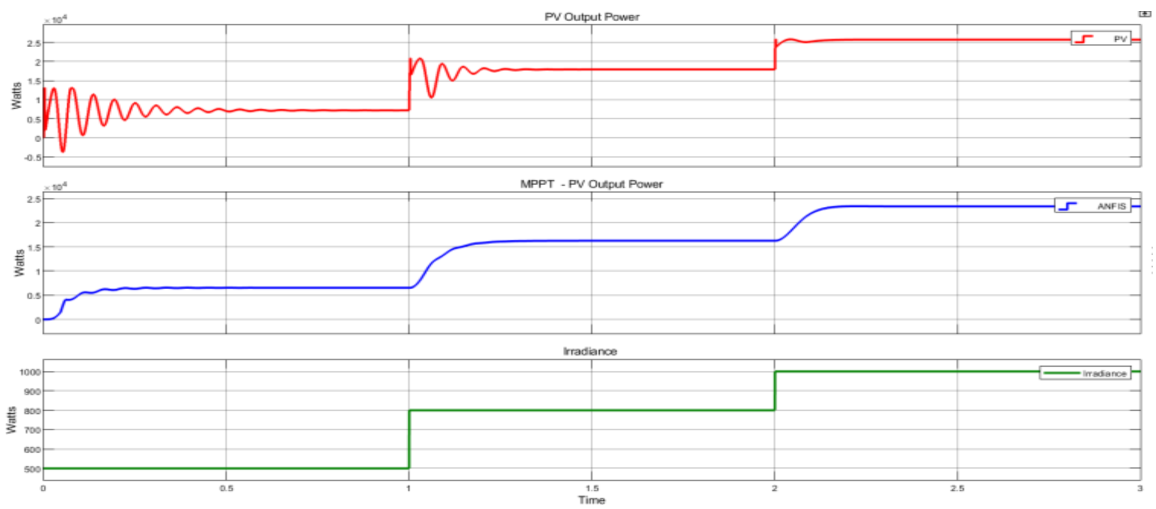
The solar (PV) power output and MPPT of the solar power output, as well as the various solar irradiance levels applied to solar systems (500W/$m^2$, 800W/$m^2$, and 1000W/$m^2$) can be seen. During periods of inclement weather, the PV's output is lowered; nonetheless, it will boost maximum power conversion in a range of weather circumstances. The outcomes of the MATLAB simulation model are examined under various weather conditions. Figure 13(a) and Figure 13(b) show how the MFNN MPPT assessed PV power output under varied weather circumstances. As shown in Figure 14, MATLAB was used to develop the proposed MFNN-based grid integration of the photovoltaic system.

Training (80%), testing (10%), and validations (10%) are provided by more than 60000 datasets (10%). Figure 15 illustrates the proposed MFNN's performance. The suggested system's greatest validation performance is 1.1225 e-12 at epoch 3448 is showin in Figure 15(a). The overall performance of the suggested current regulator methods was evaluated using the following parameters, training and validation tests, and overall results (Figure 15(b)).

The constructed current regulator algorithm has been implemented in the proposed PV-connected inverter for synchronising into the electrical grid. Figure 16 shows the simulation results of the proposed system. According to Figure 16(a), the simulation results are analysed under varying solar power and at constant load power (Battery under the SoC and SoD shown). Voltage and current waveforms of the solar system and the electricity grid are shown in Figure 16(b). Figure 17 depicts the 3-phase THD of PCC voltage and current waveforms and the values are given in Table 3.

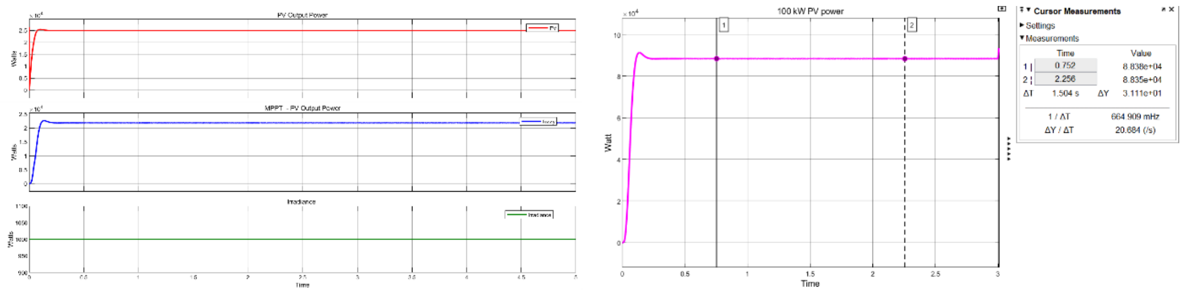



(a)




(b)

Figure 12. 100 kW PV system's (a) MFNN-MPPT Simulink model and (b) PV output power Vs. MPPT power at various irradiances




(a) (b)

Figure 13. MFNN PV power output at (a) MPPT and (b) proposed algorithm's converter output power

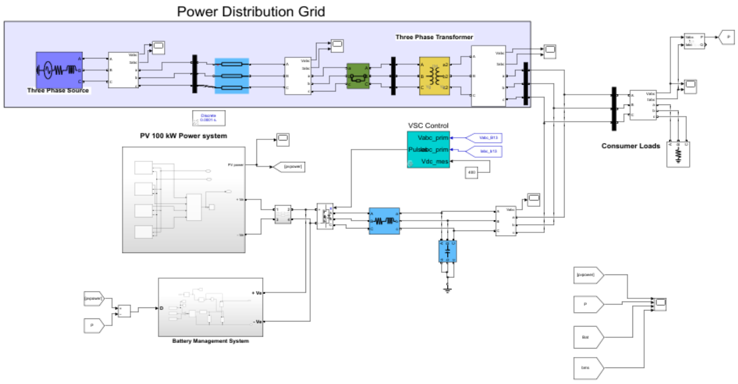
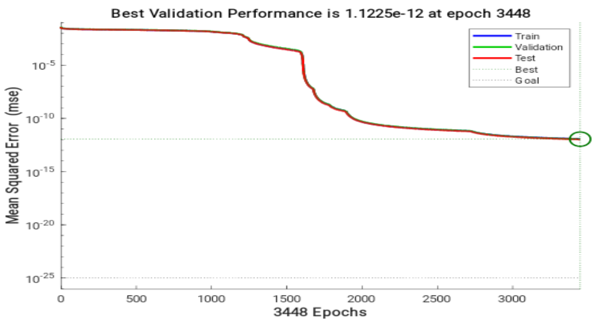
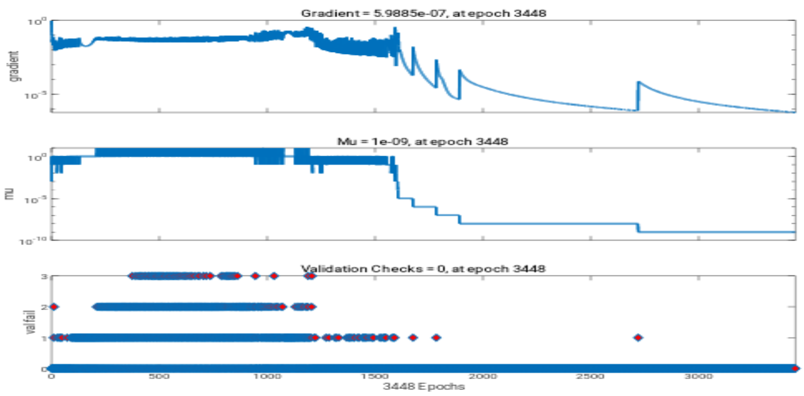



Figure 14. Grid connected solar (PV) and BMS simulation model

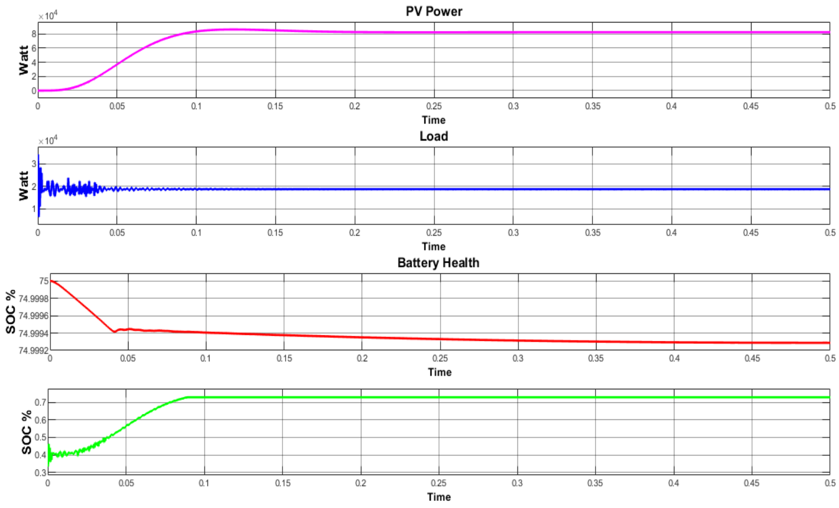



(a)

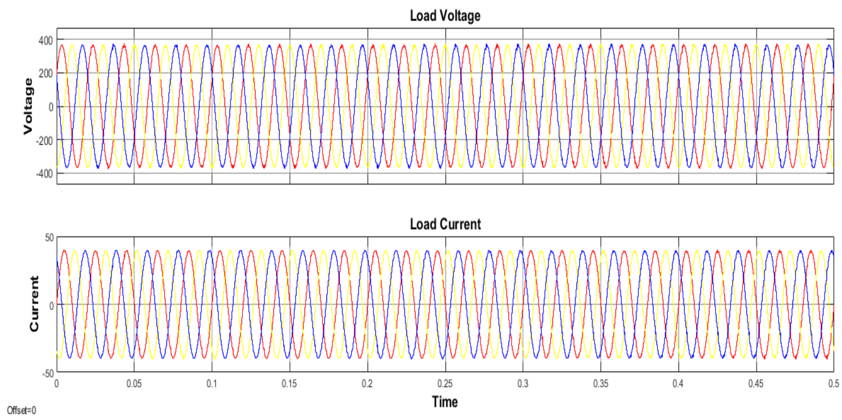



(b)

Figure 15. Proposed MFNN's (a) The best validation performance and (b) The gradient, mean and validation checks for photovoltaic system

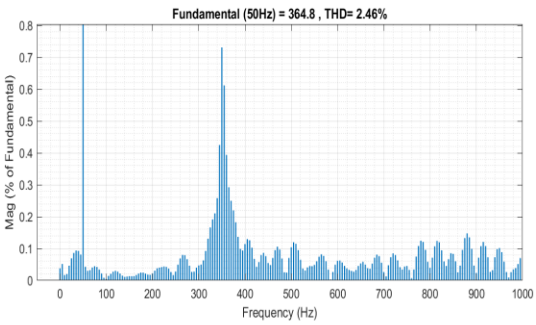



(a)

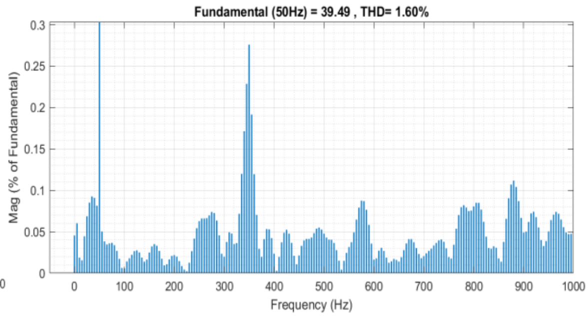



(b)

Figure 16. Simulation results of (a) battery SoC, SoD at variable solar power and constant load and (b) distributed grid voltage and current waveform




(a)




(b)

Figure 17. THD level at (a) load voltage and (b) load current

Table 3. Total harmonic distortion values

| Sl. no | THD | In percentage (%) | | THD IEEE 519 Standards |
|---|---|---|---|---|
| | | ANFIS | MFNN | |
| 1 | Voltage values | 3.45 | 2.46 | < 5% |
| 2 | Current values | 1.73 | 1.60 | < 5% |

## 5. CONCLUSIONS

The MATLAB implementation of the 100 kW PV system model was the focus of this study. For a 100kW PV system the ANFIS and multilayer feedforward neural network (MFNN) algorithms were developed. The proposed method's performance was examined in various operating situations. Second, we examined how well the photovoltaic system was integrated and performed. The ANFIS and MFNN algorithms were developed to manage the battery. The results are summarized as follows: i) Solar panels and energy storage devices have been integrated into the grid using the suggested battery management system (BMS). The recommended approach for battery load (SoD) and discharge was backed up by (SoD); ii) Ultimately, the suggested system was put through its paces under various operating situations, and the results are provided. The test results show that THD for the MFNN voltage profile is 2.46% and the current profile is 1.60%; iii) And these valus for ANFIS model are 3.45% and 1.73%, respectively, and it has been observed that MFNN yields better results than ANFIS; and iv) To show the efficiency of the suggested method, simulation results are analysed in line with IEEE 519 standards.

## ACKNOWLEDGEMENTS

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## REFERENCES


[1] M. Faisal, M. A. Hannan, P. J. Ker, A. Hussain, M. Bin Mansor, and F. Blaabjerg, “Review of energy storage system technologies in microgrid applications: Issues and challenges,” *IEEE Access*, vol. 6, pp. 35143–35164, May 2018, doi: 10.1109/ACCESS.2018.2841407.

[2] D. P. Ananthu and K. Neelshetty, “Prominent smart grid measurements by RAP-NN to warrant the reliability of the PV system,” *Energy Sources, Part A: Recovery, Utilization and Environmental Effects*, 2019, doi: 10.1080/15567036.2019.1672836.

[3] R. Indumathi, M. Venkateshkumar, and R. Raghavan, “Integration of D-Statcom based photovoltaic cell power in low voltage power distribution grid,” in *IEEE-International Conference On Advances In Engineering, Science And Management (ICAESM - 2012)*, Jun. 2012, pp. 460–465.

[4] B. Liu *et al.*, “An AC-DC hybrid multi-port energy router with coordinated control and energy management strategies,” *IEEE Access*, vol. 7, pp. 109069–109082, 2019, doi: 10.1109/ACCESS.2019.2933469.

[5] M. Venkateshkumar and R. Indumathi, “Comparative analysis of hybrid intelligent controller based MPPT of fuel cell power system,” in *2017 IEEE International Conference on Smart Technologies and Management for Computing, Communication, Controls, Energy and Materials (ICSTM)*, Aug. 2017, pp. 155–159, doi: 10.1109/ICSTM.2017.8089143.

[6] T. Hemanand, N. P. Subramaniam, and M. Venkateshkumar, “Comparative analysis of intelligent controller based microgrid integration of hybrid PV/wind power system,” *Journal of Ambient Intelligence and Humanized Computing*, 2018, doi: 10.1007/s12652-018-0961-6.

[7] L. Zaghba *et al.*, “An enhancement of grid connected PV system performance based on ANFIS MPPT control and dual axis solar tracking,” in *2019 1st International Conference on Sustainable Renewable Energy Systems and Applications (ICSRESA)*, Dec. 2019, pp. 1–6, doi: 10.1109/ICSRESA49121.2019.9182591.

[8] S. A. Lakshmanan and M. Venkateshkumar, “Analysis and design of lead-lag controller and fuzzy logic controller for boost converter applicable to RES,” in *2020 International Conference on Power, Energy, Control and Transmission Systems (ICPECTS)*, Dec. 2020, pp. 1–6, doi: 10.1109/ICPECTS49113.2020.9337004.

[9] S. Zhou, Z. Hu, W. Gu, M. Jiang, and X.-P. Zhang, “Artificial intelligence based smart energy community management: A reinforcement learning approach,” *CSEE Journal of Power and Energy Systems*, 2019, doi: 10.17775/CSEEJPES.2018.00840.

[10] N. Hamouda, B. Babes, S. Kahla, A. Boutaghane, A. Beddar, and O. Aissa, “ANFIS controller design using PSO algorithm for MPPT of solar PV system powered brushless DC motor based wire feeder unit,” *2020 International Conference on Electrical Engineering (ICEE)*, Sep. 2020, doi: 10.1109/ICEE49691.2020.9249869.

[11] B. Xu *et al.*, “Modeling a pumped storage hydropower integrated to a hybrid power system with solar-wind power and its stability analysis,” *Applied Energy*, vol. 248, pp. 446–462, Aug. 2019, doi: 10.1016/j.apenergy.2019.04.125.

[12] R. O. Gratela *et al.*, “Neuro-fuzzy based MPPT for solar PV panel hybrid cooling system,” in *2019 IEEE 11th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management ( HNICEM )*, Nov. 2019, pp. 1–6, doi: 10.1109/HNICEM48295.2019.9073356.

[13] C. S. Chin, J. Xiao, A. M. Y. M. Ghias, M. Venkateshkumar, and D. U. Sauer, “Customizable battery power system for marine and offshore applications: trends, configurations, and challenges,” *IEEE Electrification Magazine*, vol. 7, no. 4, pp. 46–55, Dec. 2019, doi: 10.1109/MELE.2019.2943977.

[14] N. T. Mbungu, R. M. Naidoo, R. C. Bansal, and V. Vahidinasab, “Overview of the optimal smart energy coordination for microgrid applications,” *IEEE Access*, vol. 7, pp. 163063–163084, 2019, doi: 10.1109/ACCESS.2019.2951459.

[15] D. Reddy and S. Ramasamy, “An artificial intelligent mppt controller based three level sepic topology for 1.2 kw solar pv system,” in *2019 Innovations in Power and Advanced Computing Technologies (i-PACT)*, Mar. 2019, pp. 1–6, doi: 10.1109/i-PACT44901.2019.8960135.

[16] S. Almazrouei, A.-K. Hamid, and M. Shamsuzzaman, “Predictive energy management in large-scale grid connected PV-batteries system,” in *2018 5th International Conference on Renewable Energy: Generation and Applications (ICREGA)*, Feb. 2018, pp. 315–318, doi: 10.1109/ICREGA.2018.8337601.

[17] G. K. Venayagamoorthy, R. K. Sharma, P. K. Gautam, and A. Ahmadi, “Dynamic energy management system for a smart microgrid,” *IEEE Transactions on Neural Networks and Learning Systems*, vol. 27, no. 8, pp. 1643–1656, Aug. 2016, doi: 10.1109/TNNLS.2016.2514358.

[18] Y. Xu and X. Shen, “Optimal control based energy management of multiple energy storage systems in a microgrid,” *IEEE Access*, vol. 6, pp. 32925–32934, Jun. 2018, doi: 10.1109/ACCESS.2018.2845408.

[19] W. Jiang, K. Yang, J. Yang, N. Xue, and Z. Zhuo, "Energy management strategy for maximization of renewable energy consumption in multi-microgrids," in *2019 6th International Conference on Systems and Informatics (ICSAI)*, Nov. 2019, pp. 325–329, doi: 10.1109/ICSAI48974.2019.9010441.

[20] V. Suresh, P. Janik, J. M. Guerrero, Z. Leonowicz, and T. Sikorski, "Microgrid energy management system with embedded deep learning forecaster and combined optimizer," *IEEE Access*, vol. 8, pp. 202225–202239, 2020, doi: 10.1109/ACCESS.2020.3036131.

[21] K. Amara *et al.*, "Improved performance of a pv solar panel with adaptive neuro fuzzy inference system anFIS based MPPT," in *2018 7th International Conference on Renewable Energy Research and Applications (ICRERA)*, Oct. 2018, pp. 1098–1101, doi: 10.1109/ICRERA.2018.8566818.

[22] K. K. Jaladi, S. Kumar, and L. M. Saini, "ANFIS controlled grid connected electric vehicle charging station using PV source," *2020 First IEEE International Conference on Measurement, Instrumentation, Control and Automation (ICMICA)*, Jun. 2020, doi: 10.1109/ICMICA48462.2020.9242717.

[23] A. M. Farayola, Y. Sun, and A. Ali, "Optimization of PV systems using linear interactions regression MPPT techniques," in *2018 IEEE PES/IAS PowerAfrica*, Jun. 2018, pp. 545–550, doi: 10.1109/PowerAfrica.2018.8521064.

[24] N. Priyadarshi, V. K. Ramachandaramurthy, S. Padmanaban, F. Azam, A. K. Sharma, and J. P. Kesari, "An ANFIS artificial technique based maximum power tracker for standalone photovoltaic power generation," in *2018 2nd IEEE International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES)*, Oct. 2018, pp. 102–107, doi: 10.1109/ICPEICES.2018.8897386.

[25] D. P. Ananthu and K. Neelashetty, "A study of 100kWp PV plant output power forecasting: A case study," 2021 *5th International Conference on Computing Methodologies and Communication (ICCMC)*, 2021, doi: 10.1109/ICCMC51019.2021.9418418.


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