

RESEARCH ARTICLE

ANFIS-Based Energy Management for a Grid-Connected PV-Battery Hybrid System at Renewable Energy Integration Demonstrator of Indonesia

Ainur Rosyid Ridho¹, Feby Agung Pamuji^{*}, Vita Lystianingrum¹ Department of Electrical Engineering, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia^{*}Corresponding author (feby@ee.its.ac.id)

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Abstract

This paper presents the design and performance evaluation of an Adaptive Neuro-Fuzzy Inference System (ANFIS)-based Energy Management System (EMS) for a grid-connected PV–battery hybrid system. The proposed EMS aims to coordinate the power exchange among the photovoltaic (PV) array, battery storage, and the utility grid to ensure reliable operation and optimal renewable utilization. The ANFIS controller receives three inputs PV power, load power, and battery state of charge (SOC) and generates the battery reference power ($P_{ref,bat}$) to regulate the charging and discharging processes. The system was trained using approximately 1600 data sets, with 30% used for testing and checking, achieving a final root-mean-square (RMS) error of 0.0081. The proposed control strategy was validated through three test scenarios: (1) constant load with variable irradiance, (2) variable load with constant irradiance, and (3) simultaneous variations of load and irradiance. Simulation results show that the ANFIS-based EMS effectively maintains power balance, prevents battery overcharge or deep discharge, and stabilizes SOC within the 30–80% range. In addition, the controller efficiently manages power sharing between the PV system, battery, and grid, ensuring optimal energy utilization and reduced grid dependency. Overall, the results confirm that the proposed EMS demonstrates adaptive, stable, and intelligent performance suitable for smart microgrid applications.

Keywords: ANFIS, battery, energy management, PV, renewable energy

I. INTRODUCTION

The utilization of renewable energy has become a key solution for providing clean power amid the growing population and industrial activities. Solar energy through photovoltaic (PV) systems is widely used due to its environmental benefits and ease of implementation [1]. However, the intermittent of solar energy requires battery storage to maintain the continuity of power supply. Therefore, in grid-connected PV–battery hybrid system, an effective Energy Management System (EMS) is essential to regulate power flow and ensure system stability and efficiency.

Energy Management System (EMS) plays an important role in optimizing the performance of hybrid power generation systems. The EMS enables real-time energy distribution and coordination between energy sources and electrical loads [2]. In previous research [3], energy management was implemented on a hybrid system consisting of PV, wind, and battery units to minimize operational costs and maximize power generation efficiency. Another study [4],[5], proposes a MILP-based strategy to optimize power allocation in a PV-based HESS while minimizing total costs, compared with a rule-based approach. Other research has also applied for managing charging and discharging in renewable energy systems.

The application of Neural Networks in energy management provides adaptive and intelligent control. Research in [6] demonstrated their effectiveness in grid-

connected PV–battery charging stations for maximizing PV utilization and predicting renewable generation, while studies such as [7] showed that Neural-Network-based controllers can dynamically manage battery–supercapacitor HESS by considering SOC variations and achieving fast power distribution typically under one second to enhance overall system performance.

Energy management systems must be capable of handling dynamic changes. Fuzzy Logic has been introduced as a rule-based control approach that effectively manages complex systems without relying on historical data. In [8], Fuzzy Logic was applied to a hybrid PV–wind–battery system using 25 rule-based controls to reduce power fluctuations. Furthermore, in [9], Fuzzy Logic was implemented to regulate the charging and discharging intervals of a wind–battery–grid system using 20 fuzzy rules, improving system stability and energy balance.

The limitation of conventional fuzzy logic in generating effective rule sets to handle uncertainties in renewable energy systems has encouraged the use of the *Adaptive Neuro-Fuzzy Inference System* (ANFIS) as a more optimal approach [10]. Several studies have demonstrated that ANFIS outperforms traditional control methods in terms of convergence speed, steady-state error, and adaptability to variations in load and solar irradiation [11].

In [12] ANFIS was applied to a grid-connected microgrid to adaptively manage battery charging and discharging power, thereby minimizing power exchange with the main grid. Similarly, an ANFIS-based controller achieved faster

dynamic response and higher efficiency compared to conventional fuzzy and ANN controllers in real-time renewable energy operations [13].

Previous ANFIS-based energy management systems for PV–battery applications mainly focus on DC bus voltage regulation. This study develops an ANFIS-based EMS for a dual inverter PV–battery system connected to a 20 kV grid, where the battery inverter operates under P–Q control and the active power reference is generated by the EMS. By shifting ANFIS from DC-side voltage stabilization to AC-side active power management, the proposed EMS thereby enhancing renewable energy utilization and reduces power exchange with the grid.

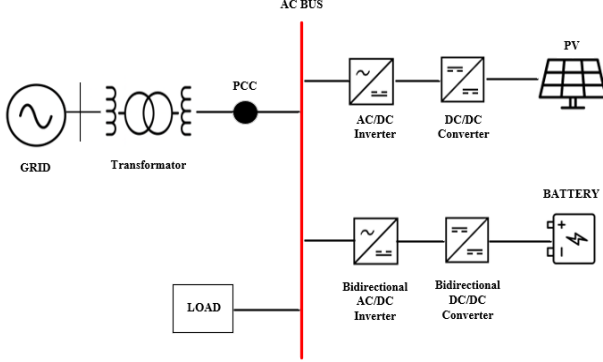


Fig. 1. Grid Connected System

II. METHODS

A. Grid-Connected Hybrid System

Fig. 1 shows the grid-connected hybrid renewable energy system developed in this study, which consists of photovoltaic (PV) panels, a lithium-ion battery energy storage system (BESS), and the utility grid. Each subsystem operates with three-phase inverter, and both inverters are connected to a common AC bus at the point of common coupling (PCC). The PCC is linked to the 20 kV distribution grid through a step-up transformer.

The system consists of the following equipment:

- 300-kW PV array with a P&O MPPT controller
- Lithium-ion battery with capacity 193.6 kWh and rated power 100 kW
- Two three phase inverters coupled to the same AC bus at the PCC
- 400V/20 kV step up transformer for grid interconnection

This grid-connected PV-battery hybrid system is implemented in a MATLAB/Simulink to analyze system behavior under different irradiance and load conditions.

B. PV Panels

In this hybrid architecture, the PV subsystem is the main power supply, which is rated at 300 kW. PV parameters are based on the Trina Solar TSM-550DE19 datasheet; thus the simulation results are expected to be realistic. The system consists of 21 modules arranged in a series with 26 strings in the parallel configuration. Table 1 lists the other parameters.

The DC-DC converter is used to increase the PV voltage and to keep the DC bus voltage levels stable, which is also controlled by a Perturb and Observe (P&O) based Maximum

Power Point Tracking (MPPT) algorithm. The PV voltage and current are monitored continuously by the P&O to keep the operating point at the maximum power point (MPP).

Table 1 PV Specification

Parameters	Value
Maximum Power(W)	549.84
Cells per module	110
Openncircuit voltagee(V)	37.9
Short-circuit currentt(A)	18.52
Voltage at maximum power pointt	31.6
Current at maximum.power pointt	17.4

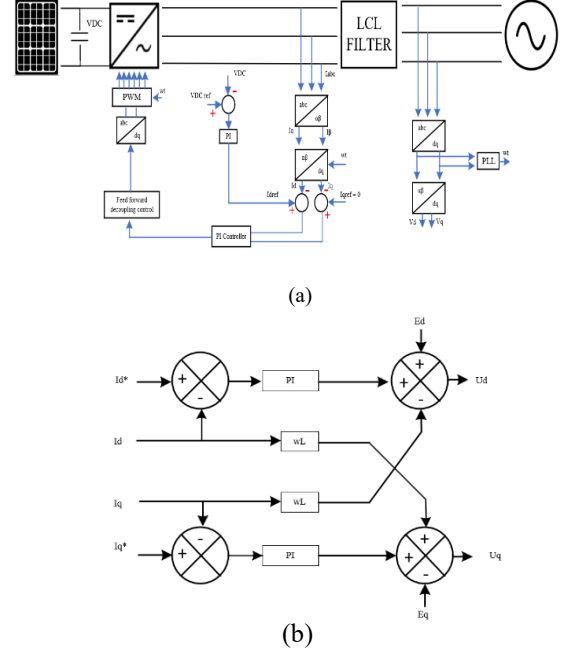


Fig. 2(a) Feed-forward decoupling control of voltage source converter, (b). inner-loop current controller.

Figure 2 (a) illustrates the control logic of the voltage source converter. The three-phase grid-connected inverter of the PV system is designed to convert the regulated DC voltage from the boost converter into AC power synchronized with the utility grid. The inverter operates under a feed-forward decoupling current control strategy with a switching frequency of 20 kHz, allowing independent control of active and reactive power. The three-phase grid voltages are assumed to be balanced and sinusoidal, which can be expressed as:

$$e_a = E \cos(\omega t) \quad (1)$$

$$e_a = E \cos\left(\omega t - \frac{2\pi}{3}\right) \quad (2)$$

$$e_b = E \cos\left(\omega t - \frac{2\pi}{3}\right) \quad (3)$$

where E is the amplitude of the grid phase voltage and ω is the grid angular frequency.

Assuming a symmetrical three-phase system, the dynamic behavior of the inverter and the filter can be described as:

$$\begin{bmatrix} \frac{di_a}{dt} \\ \frac{di_b}{dt} \\ \frac{di_c}{dt} \end{bmatrix} = \begin{bmatrix} -\frac{R}{L} & 0 & 0 \\ 0 & -\frac{R}{L} & 0 \\ 0 & 0 & -\frac{R}{L} \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \frac{1}{L} \begin{bmatrix} u_a - e_a \\ u_b - e_b \\ u_c - e_c \end{bmatrix} \quad (4)$$

where R and L are the resistance and inductance of the filter, and $u_{a,b,c}$ and $e_{a,b,c}$ represents the inverter and grid voltages, respectively.

To simplify the control structure, the three-phase currents are transformed from the abc stationary reference frame into the synchronously rotating dq frame using the Park transformation. The mathematical model in the dq reference is then written in Equation 5.

$$\begin{bmatrix} \frac{di_d}{dt} \\ \frac{di_q}{dt} \end{bmatrix} = \frac{1}{L} \begin{bmatrix} -R & \omega L \\ -\omega L & -R \end{bmatrix} \begin{bmatrix} i_d \\ i_q \end{bmatrix} - \frac{1}{L} \begin{bmatrix} e_d \\ e_q \end{bmatrix} + \frac{1}{L} \begin{bmatrix} u_d \\ u_q \end{bmatrix} \quad (5)$$

Here, i_d and i_q are the direct- and quadrature-axis current components, while e_d , e_q and u_d , u_q represent the grid and inverter voltages in the dq frame.

The control objective is to regulate the d -axis current to control the active power injected into the grid and to maintain the q -axis current at zero for unity power factor operation. A Proportional-Integral (PI) controller combined with a feed-forward decoupling term is implemented to eliminate coupling effects between both axes, improving the transient response of the inner current loop. The control laws are given as:

$$u_d = \left(K_p + \frac{K_i}{s} \right) (i_d^* - i_d) - \omega L i_q + e_d \quad (6)$$

$$u_q = \left(K_p + \frac{K_i}{s} \right) (i_q^* - i_q) - \omega L i_d + e_q \quad (7)$$

i_d^* and i_q^* are the reference currents obtained from the MPPT power reference, and K_p , K_i are the PI controller gains.

The inverse Park transformation converts the control voltages u_d and u_q back into three-phase abc form, which are processed by the sinusoidal PWM (SPWM) generator to produce switching pulses for the inverter transistors. The inverter current and grid voltage are synchronized using a Phase-Locked Loop (PLL) to maintain correct phase alignment. This control can enable accurate current tracking and stable injection power from the PV system into the grid with various irradiance conditions.

C. Batteries

The battery energy storage system is used to maintain power balance within the hybrid system. The battery charges when the PV generation exceeds the load demand or during periods of high irradiance. Conversely, it discharges when the PV output decreases or when load variations occur. In this way, the battery enhances the overall utilization of renewable energy, particularly the PV system. In this study, a lithium-ion battery with an energy capacity of 193.6 kWh and a rated power of 100 kW is used. The State of Charge (SOC) of the battery is defined by Equation 8.

$$SOC(t) = \frac{E_{batt}(t)}{E_{batt}^{Total}} \times 100 \quad (8)$$

where $E_{batt}(t)$ is the instantaneous stored energy and E_{batt}^{Total} is nominal capacity. The SOC operating range is constrained between 30% and 80% to extend

d battery lifetime and prevent overcharge or deep discharge conditions.

The control scheme for the bidirectional DC-DC converter, which is attached to the battery and controls the DC-link voltage of the battery inverter, is shown in Figure 3. The reference DC voltage V_{ref} is compared with the measured DC-link voltage V_{dc} , and the resulting voltage error is addressed by a PI controller. The output of the PI controller is sent to the PWM block to control the switching devices S_1 and S_2 , which allow bidirectional power flow in the battery charge and discharge processes. This approach to control keeps the DC-link voltage under constant regulation despite changes in the operating environment.

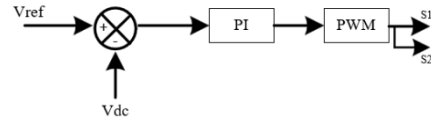


Fig. 3 Bidirectional DC-DC control

The charging and discharging behavior of the battery are governed by the reference power ($P_{ref,bat}$), which is generated by the Energy Management System based on ANFIS. The EMS processes real-time data of PV power (P_{PV}), load power (P_{load}), and battery SOC to determine the optimal $P_{ref,bat}$ that minimizes power exchange with the grid. The signal $P_{ref,bat}$ is then used as the active power reference for the battery inverter, which regulates current flow in accordance with this command. The overall structure and signal interaction of the ANFIS-based EMS are illustrated in Figure 4.

The outer control loop converts the reference active and reactive power (P_{ref} and Q_{ref}) into the corresponding current references in the synchronously rotating dq reference frame. The relationship between active/reactive power and dq currents can be expressed as:

$$\begin{bmatrix} P \\ Q \end{bmatrix} = \frac{3}{2} \begin{bmatrix} V_d & V_q \\ V_q & -V_d \end{bmatrix} \begin{bmatrix} i_d \\ i_q \end{bmatrix} \quad (9)$$

From this relationship, the reference currents are obtained as

$$i_{d,ref} = \frac{2 P_{ref}}{3 v_d}, i_{q,ref} = -\frac{2 Q_{ref}}{3 v_d} \quad (10)$$

where v_d and v_q are the grid voltage components in the dq frame. In this study, Q_{ref} is set to zero to ensure unity power factor operation, while P_{ref} corresponds to the active-power reference provided by the EMS.

The inner loop regulates the inverter output current using a feed-forward decoupling control method like the PV inverter. The measured dq currents are compared with their references ($i_{d,ref}$ and $i_{q,ref}$), and the error signals are processed by Proportional-Integral (PI) controllers to generate the control voltages u_d^* and u_q^* . The decoupled control equations are defined in Equation 11 and 12.

$$u_d = \left(K_p + \frac{Ki}{s} \right) (i_d^* - i_d) - \omega L i_q + e_d \quad (11)$$

$$u_q = \left(K_p + \frac{Ki}{s} \right) (i_q^* - i_q) - \omega L i_d + e_q \quad (12)$$

K_p and K_i are the proportional and integral gains, L is the filter inductance, and ω is the grid angular frequency. The cross-coupling terms $\omega L i_q$ and $\omega L i_d$ are compensated to enhance dynamic response. The reference control voltages u_d^* and u_q^* are transformed back into the three-phase stationary abc frame using the inverse Park transformation. These voltages are then modulated by the sinusoidal PWM generator to produce gate pulses for the inverter switches. The inverter is synchronized with the grid voltage through PLL to ensure accurate phase alignment.

This dual-loop control structure allows the battery inverter to follow the active-power reference from the EMS while maintaining a unity power factor. As a result, the system can efficiently charge or discharge the battery according to the operating condition while keeping the DC-link voltage stable through coordination with the bidirectional DC-DC converter.

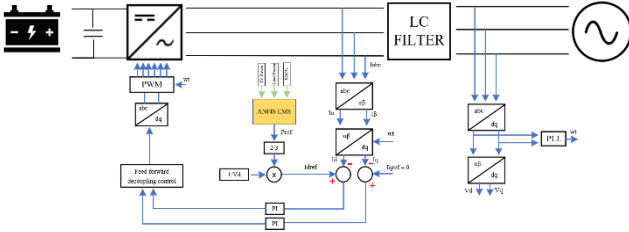


Fig. 4 ANFIS-based adaptive control of battery inverter with Feed-forward decoupling method

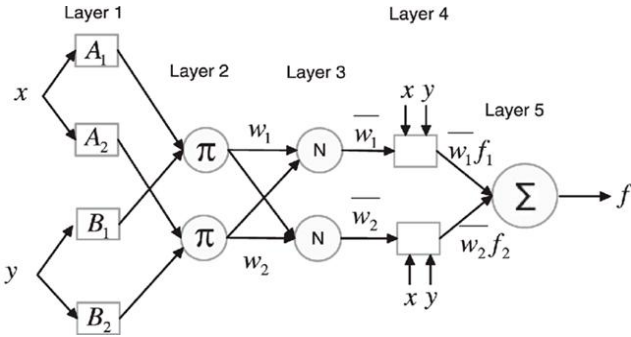


Fig. 5 ANFIS Structure

D. ANFIS-Based Energy Management System

Fuzzy Logic Control (FLC) and Artificial Neural Networks (ANNs) are widely applied in intelligent control systems due to their ability to handle nonlinearities and uncertainty. Fuzzy logic offers a rule-based structure that mimics human reasoning and does not require an exact mathematical model of the system. However, designing and tuning the membership functions (MFs) and fuzzy rules often relieve trial and error, making it time-consuming and sensitive to designer experience [14].

Merging these two techniques enables ANFIS to improve control strategies by combining neural network learning capabilities with the reasoning of fuzzy logic and human-like abilities [15]. ANFIS theoretically improves the manual

calibration of fuzzy membership functions by learning neural networks.

As presented in Figure 5 [15], the ANFIS system comprises the five layers of input, rule, normalization, defuzzification, and output, with each layer representing a particular component of the model and performing functions such as fuzzification, reasoning, and hybrid learning for parameter modification. The output result is achieved by the first-order Sugeno fuzzy model, allowing for efficient solutions to be derived quickly.

This study involves the incorporation of ANFIS into an Energy Management System (EMS) for estimating the battery reference power ($P_{ref,bat}$) based on a set of three parameters: solar power (P_{PV}), demand power (P_{load}), and the battery's state of charge (SOC). The Fuzzy Logic MATLAB Toolbox was employed for simulation and controller design. The data for training the model is created from simulation. To systematically document the operating limits of the system under different levels of solar radiation and load conditions. The generated data set aims to be as comprehensive as possible by considering all conceivable operating possibilities in practical situations.

Table 2 Data Input ANFIS

Data	PV Power	Load	SOC	(P _{bat})
1	29682	49185	100	19503
2	94133	146641	30	52508
.....				
1986	126207	98065	10	-28142
1987	135906	290819	0	0

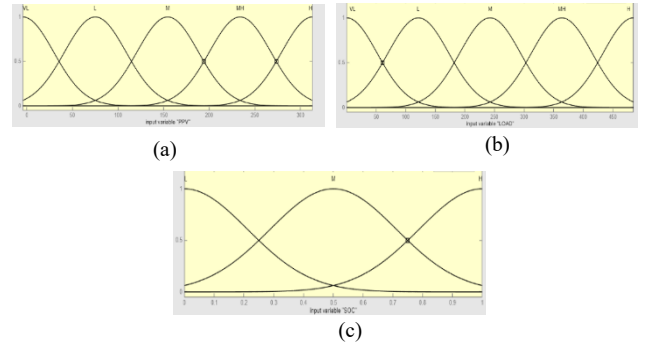


Fig. 6. MF of ANFIS. (a) P_{PV} , (b) P_{load} , (c) SOC

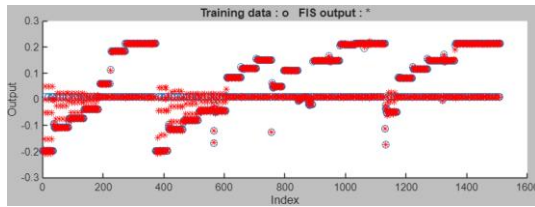
1) ANFIS Model Configuration and Training

The suggested ANFIS-based EMS allows to establish a battery reference power to control charging/discharging actions while maintaining balance of power among PV system, the load, and the grid. The ANFIS model takes the PV output power, load power, and battery SOC as its three inputs, and outputs the battery reference power (P_{bat}).

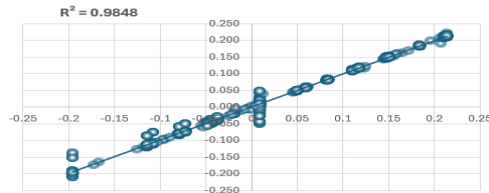
Table 2 presents datasets for ANFIS training and testing. The dataset is generated with actual REIDI system parameters including minimum and maximum operating conditions. All input and output data are normalized to range 0-1 to ensure numerical stability and improve the learning performance of the ANFIS model and divided 70% for training and 30% for testing.

The membership functions (MFs) allocated to the input variables are represented in Fig. 6. The PV and load power inputs are each represented by five Gaussian MFs: very low (VL), low (L), medium (M), high (H), and very high (VH), whereas the SOC input is represented by the three MFs of low (L), medium (M), and high (H) levels. With these fuzzy divisions, the system can provide adaptive responses compared to other systems that do not have these fuzzy partitions and instead use fixed high and low systems, enabling more flexibility in load and solar irradiance.

ANFIS makes it possible for the system to adapt to changes in solar irradiance and load demand. To evaluate the generalization capabilities of the ANFIS model, 30% of the data was allocated for testing. Training results exhibit an RMSE of 0.0081 with a regression of 0.98, as illustrated in Figure 7 (a) and (b). Figure 8 (a) and (b) illustrate RMSE and regression results of the testing phase, yielding a value of 0.0313 and 0.96. These results indicate that the ANFIS model was able to obtain the desired performance and was able to stabilize its learning and perform generalization.

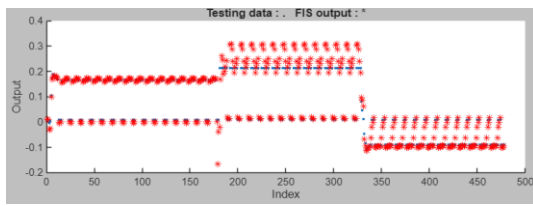


(a)

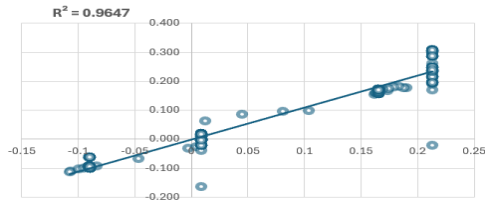


(b)

Fig. 7. (a) Training data plot, (b) Regression Result



(a)



(b)

Fig. 8. (a) Testing data plot, (b) Regression Result

Table 3 Data Output ANFIS

Data	PV Power	Load	SOC	(P _{bat})
1	45845	122390	0	0
2	173790	315978	50	100000
3	267471	218936	60	-48534

Table 3 illustrates representative input output of the trained ANFIS controller, demonstrating how the battery active power reference P_{bat} is adjusted under different operating conditions. Positive values of P_{bat} indicate battery discharging, while negative values represent charging operation.

2) Energy Management Strategy

The proposed EMS is designed to coordinate the power flow among the PV system, the battery, and the grid. Its primary objective is to maintain power balance while maximizing the utilization of renewable energy sources. The operational flow of the proposed EMS is presented in Figure 9.

At each control cycle, the EMS receives three input parameters: the PV output power (P_{PV}), the load demand (P_{load}), and the battery state of charge (SOC). The power balance is in Equation 13.

$$\Delta P = P_{PV} - P_{Load} \quad (13)$$

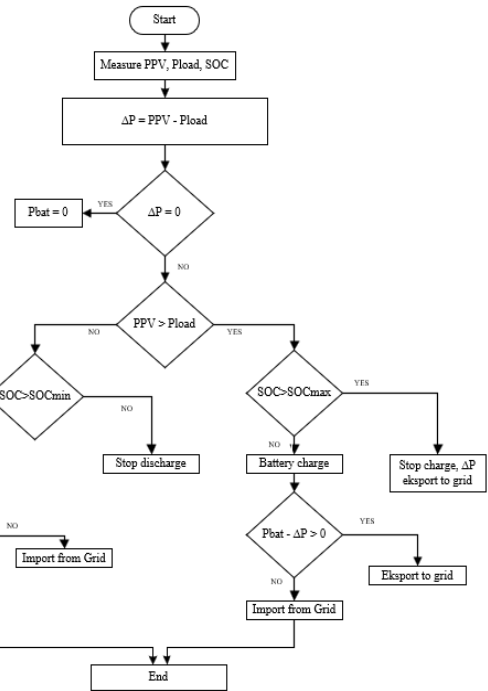


Fig. 9 Proposed EMS

This difference determines whether the generated power is sufficient to meet the load demand. When $\Delta P = 0$, the system is in equilibrium, and the battery remains idle ($P_{bat} = 0$). If $P_{PV} > P_{load}$, excess solar energy is available. The EMS first checks the battery SOC condition.

- When $SOC < SOC_{max}$, the surplus power is used to charge the battery

- When $SOC > SOC_{max}$, battery charging is stopped to prevent overcharging, and the remaining surplus power ($\Delta P > 0$) is exported to the grid

Conversely, when $P_{PV} < P_{load}$, the system experiences a power deficit. The EMS verifies whether the battery SOC is above its lower limit:

- When $SOC < SOC_{max}$, the battery discharges to compensate for the deficit
- When $SOC > SOC_{max}$, discharging is stopped to protect the battery, and the deficit is supplied by the grid (import mode).

The EMS does not directly manage the import/export activities of the grid. The EMS, via the ANFIS algorithm, only adjusts (P_{bat}) (battery active power) according to the power mismatch and SOC (State of Charge) constraints. This reference is used by the battery inverter, which operates under P-Q control such that it adjusts the P-Q (active and reactive power) output. Consequently, the battery's grid power will adjust to the power imbalance, resulting in the import or export of grid power.

This decision logic ensures that the battery operates safely within its allowable SOC range (30%–80%) while maintaining grid support whenever renewable power is insufficient. Based on the EMS flowchart, the proposed strategy differs from conventional fuzzy logic-based EMS implementations. In conventional fuzzy EMS, membership functions and rule bases must be manually designed and tuned, which is time consuming and highly dependent on expert knowledge [10]. In contrast, the proposed ANFIS-based EMS automatically learns the fuzzy rules and parameters through a training process, eliminating manual tuning while improving adaptability under varying operating conditions.

Table 4 Simulation Cases

Case	Description	Irradiance	Load Power (kW)
Case 1	Constant load, variable irradiance	200, 400, 1000, 800, 600	200
Case 2	Variable load, constant irradiance	1000	200, 230, 250, 280, 350
Case 3	Variable load and irradiance	200, 600, 1000, 400, 800	280, 100, 250, 150, 50

III. RESULTS AND DISCUSSION

This section presents the results of the proposed ANFIS-based EMS. The analysis was carried out to evaluate the performance of the EMS in regulating power flow under various operating conditions.

To fine-tune the operating of the real work environment, several tests scenarios were configured by changing the solar irradiance levels along with load demand simulations. These scenarios were used to quantify the EMS's capability to achieve power balance and control the processes of charging and discharging the battery as per the reference power formulated. Table 4 shows simulation cases with different combinations of irradiance and load variations.

A. Case 1

In the first case, the load power is kept constant at 200 kW, while the solar irradiance varies from 200 W/m² to 1000 W/m² as shown in Figure 10 (a). This test aims to evaluate the capability of the ANFIS-based EMS under conditions where the PV power output fluctuates.

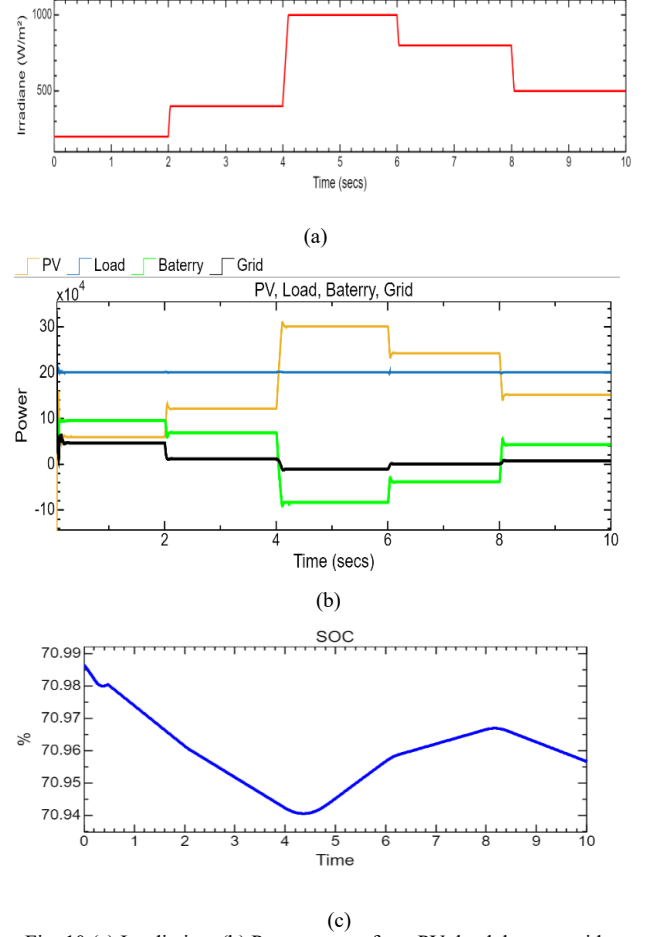


Fig. 10 (a) Irradiation, (b) Power output from PV, load, battery, grid, (c) %SOC

In Figure 10 (b), the load demand stays constant at 200 kW while solar irradiance changes between 200 and 1000 W/m². Grid power refers to the net power exchanged with the utility grid, with positive values meaning grid import (power supplied by the grid to the system) and negative values meaning grid export (power injected from the system to the grid). Grid power remains close to zero, it indicates that the load demand is supplied by the PV system and/or balanced by battery charging, resulting in negligible power exchange with the grid rather than an explicit grid power control objective. When there is low irradiance (0–4 s), there is not enough PV generation and the battery operates in discharge mode (95.41 kW and 69.5 kW), resulting in grid imports of 45 kW and 9.3 kW, respectively.

During peak irradiance (4–6 s), PV power hits 300 kW, resulting in the battery charging (–93.52 kW) and power being exported to the grid (–6.48 kW). When irradiance drops to 800 W/m² (6–8 s), the battery continues charging (–42 kW) and grid power stays around zero, meaning the load is supplied by the PV system and battery with no direct power from the grid. In the last interval (8–10 s), the

reduction in PV generation results in the battery discharging (42.9 kW), with a small grid import of 6.3 kW. The SOC profile in Fig. 10(c) follows the battery charging and discharging operation and remains within allowable limits.

B. Case 2

In the second case, we will again maintain constant solar irradiance of 1000 W/m^2 as shown in Figure 11 (a), while the power load is changed during the simulation.

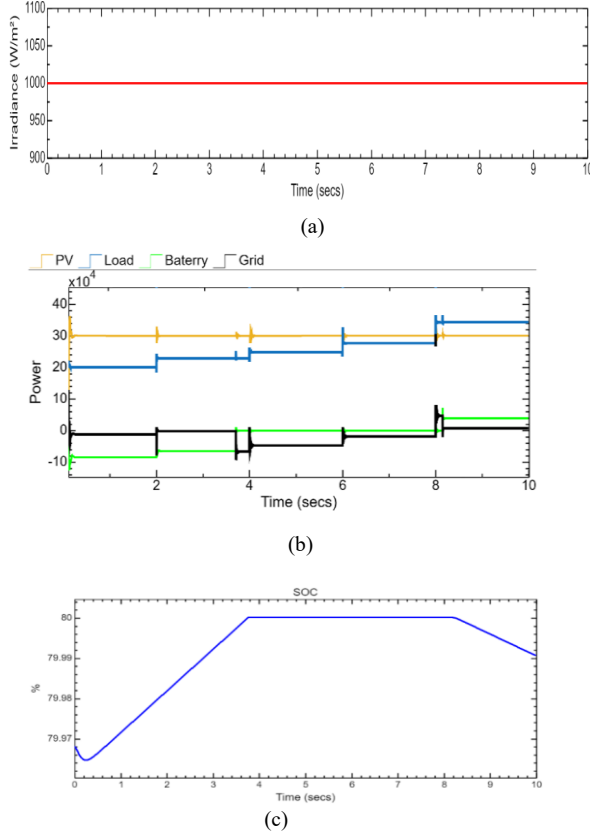


Fig. 11 (a) Irradiation, (b) Power output from PV, load, battery, grid, (c)%SOC

In Case 2, with constant solar irradiance at 1000 W/m^2 , stable PV output is 300 kW, while load demand increases from 200 kW to 350 kW as seen Figure 11 (b). Grid power is the net power exchanged with the utility grid, with positive values reflecting grid imports, and negative values reflecting grid exports. At low to moderate load conditions (0–4 s), the excess PV power is absorbed by the battery in charging mode at -93.52 kW and -64.18 kW , resulting in grid exports of -6.48 kW and -6.82 kW .

As the load increases to 250–280 kW (4–8 s), the battery power is regulated to approximately zero due to the SOC reaching its upper limit of 80%, as shown in Fig. 11(c), which prevents further charging despite the presence of surplus PV power. Consequently, the remaining surplus is exported to the grid, with grid export reaching up to -50 kW . When the load is greater than PV generation at 350 kW (8–10 s), the battery goes into discharge mode (46.53 kW), and the grid covers a small deficit of 3.47 kW. Overall grid power is kept low in relation to load changes, demonstrating that the proposed EMS effectively coordinates battery operation while respecting SOC constraints.

C. Case 3

Case 3 is designed to evaluate the performance of the proposed EMS under simultaneous variations of solar irradiance and load demand, representing a more dynamic and realistic operating condition. The temporal variation of solar irradiance applied in this case is shown in Fig. 12 (a).

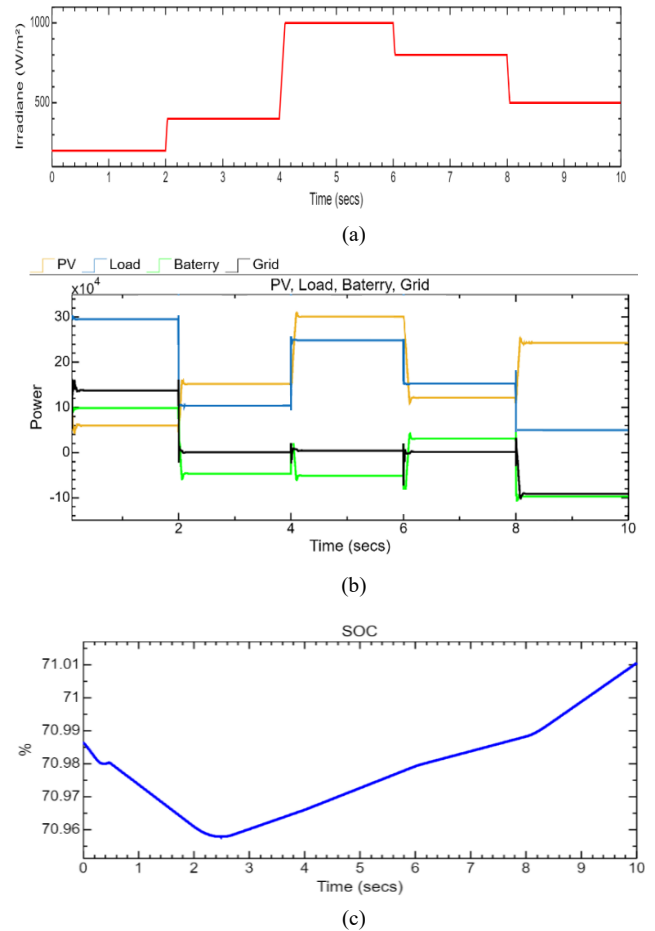


Fig. 12 (a) Irradiation, (b) Power output from PV, load, battery,grid, (c)%SOC

At the intervals of time given in figure 12(b), battery activity illustrates the interaction of the PV and the grid with the load. The first interval 0 – 2 s, shows the PV at 59.59 kW and load at 280 kW and hence, the surplus battery discharges at 98.64 kW and the grid imports at 121.77 kW. The next interval of 2 – 4 s shows an increase in irradiance and a decrease in load. The PV shifts to 151.8 kW and load at 100 kW. The surplus is absorbed by the battery, with grid power at nearly zero: battery charge mode of -51.8 kW . At 4 – 6 s, PV power reaches its peak at 300 kW, and load at 250 kW. The battery discharges 50 kW and the grid zero suggesting local balancing. During the period of 6 – 8 s, the PV power drops to 121.27 kW and load at 150 kW, balancing battery discharge of 27.17 kW and a grid increase of 1.56 kW. Finally, at 8–10 s, PV power increases to 242.3 kW and a reduction in load to 50 kW. Here the battery switches to charge mode at -98.39 kW and the surplus to the grid at -93.9 kW .

The grid power has values that quantitatively range from -93.9 kW (export) to 121.77 kW (import). During some time intervals (2–6 s) the power stays near zero, indicating the EMS successfully manages PV generation, battery operation, and demand load. Also, the the near zero grid

power results from power balance EMS as a passive outcome rather than a target of control. Battery SOC adjustments, as a result of the charging and discharging conditions, are illustrated in Fig. 12 (c).

IV. CONCLUSION

The aim of this study was to formulate an ANFIS-based EMS within a grid-connected hybrid PV-battery system. The primary target is to sustain an equilibrium of power within the system and accomplish that while decreasing utility grid dependency. The simulation data the proposed EMS succeeded in maintaining this balance, during fluctuating conditions which caused load and solar irradiance changes. The system controller works to discharge and charge the battery in an adaptive manner while maintaining the SOC within a safe operating limit. In addition, the EMS effectively reduces grid usage by prioritizing PV power and exporting surplus energy whenever available. Overall, the ANFIS-based EMS demonstrates stable operation under dynamic conditions, supporting its potential for real-time implementation in future smart microgrid applications.

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