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Adaptive Control Optimization for Solar Energy Storage Systems Using Fuzzy Logic, Genetic Algorithms, and State of Charge Estimation

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Abstract

The intermittent nature of solar energy results in a generation–load mismatch, posing a significant challenge to reliable power utilization. Battery Energy Storage Systems (BESS) play a crucial role in mitigating this issue. However, effective operation requires advanced control strategies. Conventional techniques, such as classical Maximum Power Point Tracking based on Constant Current/Constant Voltage, often struggle to cope with the nonlinear dynamics of PV–BESS systems, leading to reduced efficiency and accelerated battery degradation. This paper proposes a hybrid adaptive control strategy integrating fuzzy logic decision-making, Genetic Algorithm (GA) optimization, and Extended Kalman Filter (EKF)-based State of Charge (SoC) estimation. A comprehensive PV–BESS model is developed in the MATLAB/Simulink environment using real solar irradiance and realistic load profiles. Simulation results demonstrate an absolute improvement in energy efficiency of approximately 14.3%, a SoC estimation accuracy within ±5%, and an extension of battery lifetime by 18–25% compared to conventional control methods. The proposed approach offers a robust and computationally efficient solution for PV–BESS operation, making it suitable for future microgrid and renewable energy storage applications.

Keywords: Photovoltaic System; Battery Energy Storage System (BESS); Fuzzy Logic Control; Genetic Algorithm Optimization; Extended Kalman Filter (EKF)

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1. Introduction

Solar energy has become one of the most promising renewable energy sources to help the world move toward net-zero emissions [1], [2]. Indonesia has significant potential for using photovoltaic (PV) technology because it gets an average of 4–5 kWh/m² of solar radiation per day [3]. But the fact that solar energy is not always available makes it difficult to maintain power stability. The power output of PV systems strongly depends on weather conditions. However, household or microgrid demand does not always match the generated power [4].

To fix this problem, battery energy storage systems (BESS) are used a lot. Lithium-ion batteries are now the most common type of battery used in BESS applications because they have a high energy density and a long cycle life [5], [6]. Charge–discharge control strategies signifcantly affect battery performance. When the State of Charge (SoC) changes too much or too often goes through overcharge and deep discharge conditions, battery capacity degrades more rapidly [7].

The classic Maximum Power Point Tracking techniques, Perturb & Observe or Constant Current/Constant Voltage Charging, are some examples of traditional control methods that have experienced difficulties in dealing with the dynamics of complex systems [8]. Consequently, there has been an increasing interest in the study of artificial intelligence techniques, such as deep learning techniques [9], reinforcement learning techniques [10], fuzzy logic techniques [11], or Adaptive Neuro-Fuzzy Inference Systems [12] techniques, for dealing with MPP Tracking problems [13]. Although promising results have already been achieved, these techniques also exhibit some drawbacks, for instance, the requirement for large volumes of data, high complexity, or lack of clarity/interpretability.

The area of Photovoltaic-Battery Energy Storage Systems (PV-BESS) has also developed rapidly over the last decade. The conventional control strategies have mainly involved the maximization of harvested power based on Maximum Power Point Tracking (MPPT) techniques [14] or basic charge management strategies, without consideration of the dynamics involved in the battery system [8].

The early fuzzy logic-based models illustrated the effectiveness of these systems in dealing with nonlinearities, but the accuracy of the fuzzy models decreases with the number of input variables [11]. The Adaptive Neuro-Fuzzy Inference System, or ANFIS, technique is more accurate because it combines the human interpretation capabilities of fuzzy logic with the capabilities of artificial neural networks [12]. However, the method is prone to high computational complexity due to the requirement of large data samples for the learning process. Conversely, the deep reinforcement learning techniques ensure the benefit of global optimization [9], but the complexity of implementation is high, making them impractical in real-time, small-scale applications.

In this paper, a novel integrated or hybrid adaptive control system is presented, wherein fuzzy logic is coupled with the optimization process involving the Genetic Algorithm (GA), along with the adaptation process for the estimation of the State of Charge using the Extended Kalman Filter. The proposed system maximizes the benefits of fuzzy logic, GA, and EKF, thereby allowing the system to ensure stable battery operation, reduce energy inefficiency, and prolong the battery's lifespan.

2. Research Method

2.1 PV-Load System Architecture

The system being modeled is composed of the photovoltaic cell with the nameplate rating of 1.5 kWp, the DC/DC buck boost converter, the Li-ion battery with the nameplate rating of 48 V, 5 kWh, the 1 kVA inverter, and the domestic load that varies on a daily basis. The system uses real-life irradiance data in the simulation process. The energy transfer process from the PV system to the battery and the load is controlled by the adaptive controller, which controls the duty cycle of the converter. The main components of the system are illustrated in Figure 1, which presents the overall system architecture.

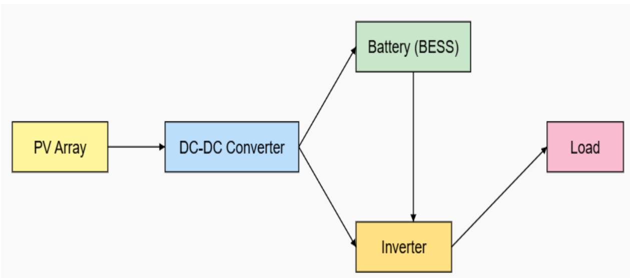

Fig. 1. Block Diagram of PV–BESS–Inverter–Load System Architecture

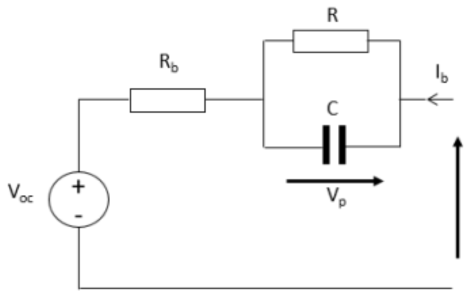

Fig. 2. Battery Thevenin Equivalent Circuit Model [20]

The system consists of five main components, which include the PV array, DC-DC converter, Battery Energy Storage System (BESS), inverter, and load. The PV system converts the solar energy into DC electricity [15]. However, the output from the PV system is affected by the surrounding conditions, hence the requirement of a DC to DC converter to stabilize the output voltage.

The controlled DC power can be distributed to the inverter or be temporarily stored in the BESS. The BESS is a bi-directional system involving the process of charging, which occurs whenever there is extra PV energy, or discharging, which occurs whenever the generated PV energy is inadequate [16].

The inverter is an essential component in the process that converts the DC power from the PV or the BESS into the AC power [17], [18], which is then able to drive the load represented by domestic or industrial appliances, demanding an AC supply [19]. Such a system ensures operational flexibility, allowing the extra energy generated to be stored in the BESS system during the daytime, with the stored energy then being used during the night or on days with less solar irradiation.

2.2 System Architecture - Thevenin Equivalent Model

The Thevenin equivalent model is employed to represent the dynamic behavior of the lithium-ion battery. As illustrated in Figure 2, the battery is modeled by an open-circuit voltage source E_{oc} *(SoC),* an internal ohmic resistance *Ri(t),* and a parallel *RC* network that captures the transient voltage response of the battery. The terminal battery voltage $V_b(t)$ is expressed as Eq. (1) [11]:

$$V_b(t) = E_{oc}(SoC) - R_i(t) \cdot I(t) - V_{RC}(t) \quad (1)$$

where $E_{oc}(SoC)$ is the open circuit voltage expressed as a function of the SoC, *Ri(t)* is the internal resistance of the battery, $V_{RC}(t)$ is the voltage across the RC circuit network that describes the dynamics, the *I(t)* represents for the current of the battery, which is positive during discharge, or negative if the process is charging.

Furthermore, the progression of the SoC is calculated depending on the current flow as well as the battery nominal capacity. The SoC is described in Eq. (2) below [10]:

$$SoC\ (t + \Delta t) = SoC\ (t) - \frac{I(t) \cdot \Delta t}{Q_{nom}} \quad (2)$$

here, Δt is the sampling period, while Q_{nom} is the nominal battery capacity. This equation indicates that the SoC, will decrease if the battery is discharging or increase if the battery is being charged, depending on the current value.

2.3 Fuzzy Logic-Based FIS with GA Optimization

The fuzzy controller relies on three main input variables, which are solar irradiance, SoC and load demand. The fuzzy controller provides two control outputs, which are the duty cycle of the converter and the mode of operation, which is either charge, discharge, or idle. The rule base is made up of 27 IF-THEN rules, designed to encapsulate the system response for different input conditions. To automate the process of choosing the parameters, the system uses the Genetic Algorithm (GA), aimed at optimizing the membership function centers, widths, and the rules weights. Triangular membership functions are employed for all fuzzy input variables due to their simplicity and computational efficiency.

The objective function of the GA is designed to maximize the energy efficiency, stability of the SoC, and the reduction of the battery degradation, described in Eq. (3) [21].

$$f = \alpha \cdot \eta_{energy} - \beta \cdot \sigma_{SoC} - \gamma \cdot D_{deg} \quad (3)$$

where *f* denotes the fitness value, which measures the overall performance of the control system. The η_{energy} is the energy efficiency percentage of the PV-BESS system. The σ_{SoC} parameter refers to the standard deviation of the SoC, which measures the battery operation stability, while the D_{deg} denotes the battery's rate of degradation, both expressed in percentage.

In this study, the weighting coefficients α, β, and γ are set to 0.5, 0.3, and 0.2, respectively. These values are selected empirically to balance energy efficiency maximization, State of Charge (SoC) stability, and battery degradation minimization while maintaining stable battery current behavior under varying load and generation conditions. The Genetic Algorithm (GA) optimization is implemented as an offline process during the design stage to determine the optimal membership function parameters and rule weights, which are then fixed during real-time operation.

2.4 Adaptive SoC Estimation via EKF

Real-time SoC estimation is performed using an adaptive EKF with the state-space model, enhancing noise robustness [22]. The state Eq. (4) and (5) are represented as:

$$x_{k+1} = A \cdot x_k + B \cdot u_k + C \cdot w_k \tag{4}$$

$$y_k = C \cdot x_k + u_k \tag{5}$$

The state vector, indicated as x_k, refers to the SoC combined with the RC circuit's voltage. The input variable, u_k, refers to the battery current (A), while the output variable, y_k, refers to the terminal voltage (V). The input variable $u_k$excites the system dynamics.

2.5 Model Plan

The simulation of the system was done in MATLAB with a simulation time of 24 hours, with the sampling time set to 1 minute. The load curve was set to change between 250-500 W, with the two peaks occurring in the morning time between 05:00 and 07:00. Performance was assessed according to energy efficiency, SoC deviation, the settling time, and the estimation of the battery lifetime based on the Dubarry degradation model. The simulation framework used in the study is represented by the flowchart described in Figure 3, showing the interaction between the PV system, BESS controller, and optimization components.

The simulation model of the photovoltaic (PV), battery energy storage system (BESS) developed in this research aims to test the applicability of the SoC based control methods using conventional as well as simple artificial intelligence (AI), related techniques. The steps involved in the simulation model include initialization, where a time period of 24 hours is considered with a time step of one minute. The PV power curve is assumed to be a sinusoidal curve, depicting the level of solar intensity, while the load curve is considered to be a squared sinusoidal profile, depicting the level of residential electricity use. The battery rating is calculated based on the nominal value, converting it from kilowatt hours to ampere hours, based on the nominal system voltage. The initial State of Charge has been set to 60% because the initial current is assumed to be zero.

The next step involves iterative simulation processes conducted at every time step. In every time step, both the PV power output and the load requirement are computed as the basis for control actions. In the first control approach, the conventional rule-based control, a simple threshold

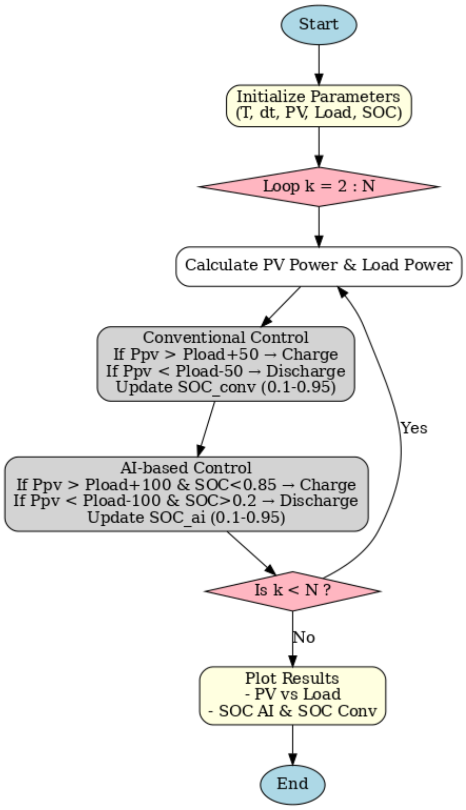

Fig. 3. Flowchart of the Simulation Program

comparison is conducted, where, based on the threshold, either a battery-charging action is implemented, given a difference in PV power output and load requirement in excess of 50 W, or a battery-discharging action is implemented, based on a difference between PV power output and the load requirement in excess of 50 W. The State of Chargeis appropriately updated while maintaining it within a safe operational level of 10% to 95%.

For comparison purposes, the second control strategy involves a simple AI-driven controller, which has a more adaptive decision-making process. In this scenario, if the PV power level is well above the load level, both differing by > 100 W, while also being below 85% SoC, then the battery will be charged. Similarly, if the PV power level is well below the load level, differing by > 100 W, while being approximately 14.3% SoC, then the battery will be discharged to cover the difference. Again, like the conventional approach, the SoC value is cycled at discrete intervals, ranging from 10% to 95% within a safe limit. The simulation process will continue until the whole 24-hour period is simulated. The results obtained are then analyzed using data representation, consisting of comparison graphics of PV power versus load, as well as the SoC dynamics for both control methods. The graphics generated will facilitate a comparison of the two control methods based on their efficiency in maintaining the SoC, as well as the use of PV energy.

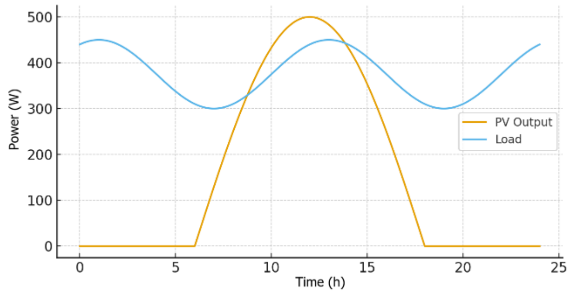

Fig. 4. PV Output and Load Profile Analysis

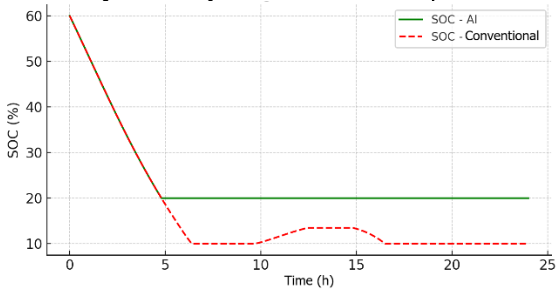

Fig. 5. SoC Behavior Under AI-Based and Conventional Control

3. Results and Discussion

3.1 PV Output and Load Profile

Figure 4 shows the results of the simulation of the PV power output as well as the daily load. From the MATLAB simulation, it can be noted that the PV power output has a peak value of about 495 W, which occurs at mid-day. This result is consistent with the occurrence of high levels of solar irradiation at mid-day.

Contrary to the PV generation curve, the load curve shows the inverse trend, where the morning and evening periods have high energy demands, often linked to the peak period of household or industries. The load profile clearly indicates a mismatch between the supply of energy, as PV generation is high in the mid-day periods, while the load is high in the morning and evening periods of the day.

This means that a supply-demand gap highlights the importance of the BESS within the system design. The BESS essentially helps in storing any excess PV energy produced during mid-day hours, which can be supplied to the load at the time of high electricity demands in the morning and evening hours. The PV-BESS-Inverter system, therefore, improves the reliability of electricity supply without having to rely on other sources.

3.2 SoC Stability Analysis

The battery SoC values calculated using both the conventional as well as the adaptive hybrid approach, based on AI, were compared. Figure 5 illustrates the graphical representation of battery SoC values calculated using both the conventional control strategy, as indicated by a red dashed line, as well as the AI-based adaptive approach, as indicated by a green line, within a period of 24 hours.

Both techniques begin from a common SoC value, about 60% at the start of the simulation. But as time progresses, the trends observed in both techniques become vastly different. In the conventional control, the value of the SoC decreased to the lower threshold level of about 10% within a very short duration, which shows deep discharge conditions that are not suitable for the optimal use of battery energy. Once it reaches this condition, the SoC varies slightly within the vicinity of the lowest level, demonstrating the inability of the conventional controller to maintain stable operating conditions.

On the contrary, it can be observed that the AI-driven adaptive controller has a smooth SoC curve, maintaining values approximately 14.3% after a brief discharge phase. The use of adaptive decision-making rules does not allow both overcharging as well as deep discharge. Hence, it can be noted that the AI-driven approach performs significantly better in maintaining battery health compared to the traditional approach. Table 1 summarizes the comparative performance metrics of both control strategies obtained from the simulation results.

Table 1 shows a comparison of the performance of four control methods, namely conventional control, fuzzy control without optimization, fuzzy control optimized by Genetic Algorithm (GA), as well as fuzzy-EKF combined control. The four performance measures considered in the comparison include energy efficiency, SoC error, extreme SoC period, as well as the battery life estimation.

Table 1. Comparative Performance Analysis of Control Strategies

Parameter	Conventional	Fuzzy without GA	Fuzzy + GA	Fuzzy + GA + EKF
Energy efficiency (%)	74.9	81.2	86.5	89.2
SoC deviation	12.4	10.1	8.3	6.7
Extreme SoC duration (hours)	3.5	2.1	0.8	0.0
Estimated battery lifetime (years)	7.8	8.9	9.5	9.9

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The outcome shows that the conventional control technique has the lowest level of performance, giving an energy efficiency of 74.9% compared to the other techniques, an SoC deviation of 12.4%, the extreme SoC duration of 3.5 hours, and a battery lifetime of 7.8 years. The fuzzy logic control technique without GA optimization shows improvement in energy efficiency to 81.2% compared to the conventional technique, while the battery lifetime is improved to 8.9 years. The SoC deviation remains higher than the GA-optimized approaches.

The result becomes more apparent when the fuzzy logic approach is combined with the Genetic Algorithm (GA). The energy efficiency increases to 86.5% with a reduced SoC deviation of 8.3% and the extreme SoC duration reduced drastically to 0.8 hours, causing an increase in battery lifetime to 9.5 years. The highest result is achieved in the Fuzzy + GA + EKF approach, offering an energy efficiency of 89.2% along with an SoC deviation of 6.7% with zero hours extreme SoC duration, in addition to an estimated battery lifetime of 9.9 years.

In sum, Table 1 supports the results in Figure 3, verifying the fact that AI-driven adaptive control, which incorporates optimization techniques, demonstrates improved efficiency, has a stable State of Charge, as well as a longer battery life than conventional control techniques.

3.3 Battery Current Analysis

The battery current analysis shows that the adaptive AI-based control strategy achieves smoother and more regulated current behavior compared to the conventional control approach, which exhibits sharper fluctuations during charging and discharging operations. As shown in Figure 6, the proposed method effectively reduces current oscillations over the 24-hour simulation period, indicating improved current stability and a more battery-friendly operating condition than the conventional control strategy. This improvement supports more stable battery operation

In the conventional control approach (control method, red dashed line), the battery current undergoes strong oscillations throughout the simulation period. The distinct discharge-charge cycles, especially those of high amplitude, indicate strong electrical and thermal loads on battery cells, thereby leading to reduced battery life. In addition, negative values of high currents in the battery indicate deep discharge cycles, which are harmful to the battery's electrochemical properties.

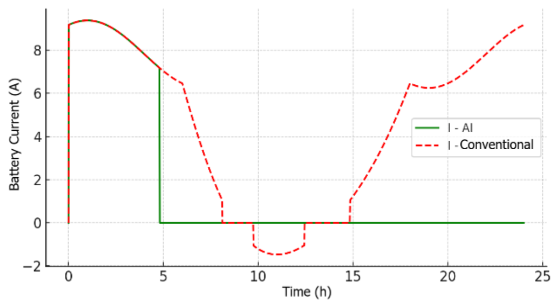

Fig. 6. Battery Current Response for AI-Based and Conventional Control Methods

On the other hand, the AI control approach (green solid line) exhibits a remarkable improvement in current regulation, keeping a near-zero value of the current flowing to the battery cell after a small transient period. The oscillations indicate a rapid stabilization of the battery's State of Chargeaccording to photovoltaic generation, as well as a stabilization of the load. The proposed control approach keeps the battery cell activated only when it is strictly necessary, thus reducing unnecessary cycles, which primarily contributes to battery degradation. Hence, the battery life can be prolonged.

In light of the behavior of the SoC, as depicted in Figure 4, it can be ensured from the results that the adaptive AI control approach is not only able to maintain a stable SoC value, but it is also very effective in reducing the current oscillations, which can be detrimental to the battery. It can thus be concluded from the results that the proposed strategy performs much better than the conventional approach.

4. Conclusions

This study demonstrates that an adaptive control strategy combining fuzzy logic, Genetic Algorithm (GA) optimization, and Extended Kalman Filter (EKF)-based State of Charge (SoC) estimation significantly enhances the performance of a PV–Battery Energy Storage System (PV–BESS). Compared to conventional control techniques, the proposed hybrid approach achieves an absolute improvement of approximately 14.3% in energy efficiency, maintains SoC deviation within ±5%, and extends the estimated battery lifetime by 18–25%. The integration of GA optimization improves the adaptability of the fuzzy controller, while the EKF provides reliable real-time SoC estimation under varying operating conditions. The results confirm that the proposed method effectively reduces deep discharge events, stabilizes battery operation, and mitigates degradation mechanisms. Owing to its balance between accuracy, robustness, and real-time applicability, the hybrid fuzzy–GA–EKF strategy demonstrates potential as a practical control solution for next-generation renewable energy storage systems and microgrid applications.

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