Smoothing Photovoltaic Power Output Fluctuation Using an Alpha-Beta Filter-Based Approach

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Abstract—**Photovoltaic (PV) power generation is inherently intermittent, as it depends on variable weather conditions, leading to output fluctuations that can compromise grid stability. To address this challenge, this study proposes a real-time PV output smoothing approach based on an Alpha-Beta filter algorithm. The method forecasts short-term power variations and dynamically regulates the charging and discharging of a Battery Energy Storage System (BESS), intervening only when significant deviations occur. This selective control reduces unnecessary cycling, improves State of Charge (SOC) management, and extends battery lifespan. Unlike conventional smoothing techniques, the proposed framework maintains the original PV generation profile while mitigating disruptive fluctuations. Implemented in Python and evaluated using OpenDSS simulations with real PV data from a high-penetration microgrid, the method achieved a 91.7% reduction in power variation and maintained voltage stability within regulatory limits. These results demonstrate the effectiveness and practicality of the Alpha-Beta filter-based strategy for stabilizing PV output and optimizing energy storage operation in distributed energy systems.**

I. Introduction

The integration of renewable energy sources, particularly solar PV systems, has accelerated globally as part of the transition toward sustainable energy. PV systems offer numerous advantages, including environmental friendliness and energy sustainability. However, their inherent variability due to weather conditions, such as cloud cover, shading, and atmospheric disturbances, introduces significant challenges to power grid stability [1]. Such fluctuations induce frequency deviations, voltage instability, and greater operational complexity across distribution networks [2]. The intermittency of PV power generation becomes more critical as its penetration level rises. Without effective mitigation strategies, excessive power fluctuations may trigger grid disturbances, leading to increased reliance on ancillary services such as spinning reserves and demand-side management [3-4]. Furthermore, these fluctuations can cause excessive wear on conventional power generation systems, leading to higher maintenance costs and reduced efficiency [5].

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To ensure the stability of power systems with high PV penetration, various power smoothing techniques have been explored. Traditional approaches include the use of BESS [6], demand response strategies [7], and advanced grid-forming inverter control methods [8]. However, these solutions often require significant infrastructure investment or complex real-time control mechanisms. Among these solutions, BESS is one of the most effective approaches for mitigating PV power fluctuations, as it can store excess energy during peak generation and release it during power deficits [9]. However, the frequent charge-discharge cycles associated with conventional BESS-based smoothing methods can degrade battery life and reduce overall system efficiency [10]. Thus, optimizing BESS operation while maintaining effective power smoothing is crucial for achieving a balance between performance and cost-effectiveness. Recent studies have investigated advanced filtering techniques to enhance PV power smoothing. The Kalman filter [11], wavelet transform [12], and artificial intelligence-based forecasting methods [13] have been employed to predict and mitigate fluctuations in PV generation. However, many of these methods either require intensive computational resources or are highly dependent on historical data and model accuracy.

To address these challenges, this paper proposes an Alpha-Beta filter-based smoothing method for mitigating PV power output fluctuations. The Alpha-Beta filter is a simple yet effective estimation technique commonly used in tracking applications [14]. It enables real-time power fluctuation prediction while maintaining computational efficiency. By applying the Alpha-Beta filter, the proposed method can dynamically regulate the charging and discharging behavior of a BESS to minimize abrupt PV power variations, thereby ensuring smoother power delivery to the grid. The key objectives of this research are as follows:

- Develop a computationally efficient PV smoothing method using the Alpha-Beta filter to reduce power fluctuation without excessive reliance on historical data.
- Optimize BESS operation by reducing unnecessary charge-discharge cycles to enhance battery lifespan while maintaining grid stability.
- Evaluate the voltage variation before and after the proposed PV smoothing method through simulations using OpenDSS [15] and practical PV generation data.

The remainder of this paper is structured as follows. Section II describes the problem and the implementation of the Alpha-Beta filter-based smoothing approach. Section III presents the mathematical model of the Alpha-Beta filter and its application in PV power smoothing. Section IV provides simulation results and performance evaluations based on practical data. Section V discusses the conclusions.

II. SYSTEM OVERVIEW AND PROBLEM DESCRIPTION

The NCUE Microgrid is a multi-microgrid system, consisting of multiple building-level microgrids. Among them, Microgrid #1 and Microgrid #2 is characterized by high PV penetration, as illustrated in Fig. 1. The total installed capacity of the rooftop PV system is 40 kW. The BESS is equipped with a 100 kW Power Conversion System (PCS) and a 50-kWh battery, enabling energy storage and grid support functions. Additionally, the regular peak load of these two microgrids is approximately 98 kW, it is high PV penetration microgrids. The variability in PV power output, primarily influenced by environmental conditions; therefore, this study proposes a PV power smoothing function that optimally regulates the charge/discharge cycles of the BESS.

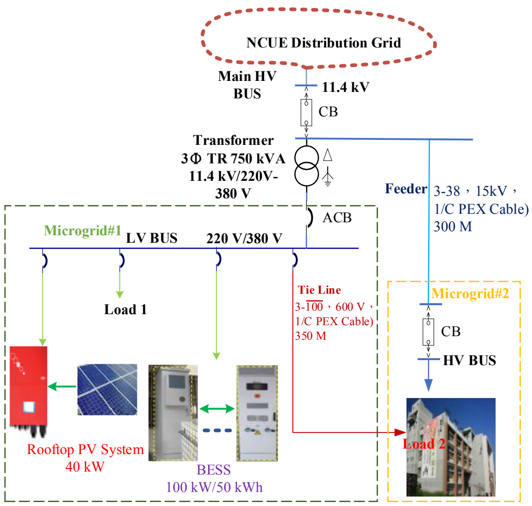


Figure 1. The NCUE Microgrid#1 & Microgrid#2 with highly PV penetration

Fig. 2 illustrates the overall architecture of the proposed PV smoothing framework, which integrates Python-based program, a power flow solver, and a data management system to implement and evaluate the smoothing method. The framework comprises the following components:

- Proposed Approach Solver: the core of the framework is a python-based solver that implements the Alpha-Beta filter algorithm. This module is responsible for processing real-time PV output data, predicting power fluctuations, calculating the required energy compensation using the BESS, and coordinating data exchange between the power flow solver and the database server.
- Power Flow Solver: this block performs detailed power flow analysis of the micrograds. It evaluates the impact of the smoothed PV output on the system's voltage profile. The Python solver sends control signals and receives simulation results.
- Database Server: the database server stores and manages historical and real-time PV generation and load data, and BESS operation logs.

In summary, the framework demonstrates a modular control system in which the Python module acts as the central decision-making unit, integrating simulation and data components to enable real-time PV power smoothing and performance evaluation.

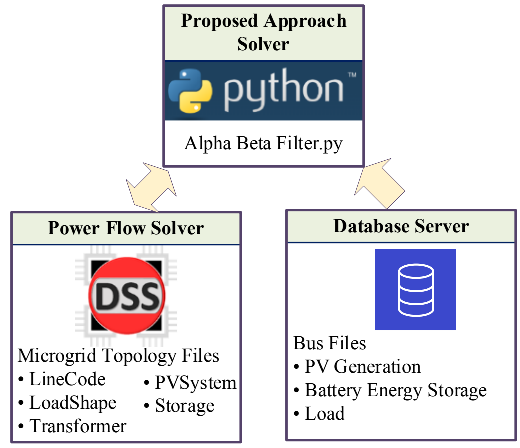


Figure 2. The Proposed PV smoothing framework

A. *Building a Distribution Network Model*

To accurately represent the NCUE Microgrid system, a detailed distribution network model is developed using OpenDSS. The model incorporates real-time and historical data to replicate the dynamic behavior of power flows across the network under varying operational conditions. The simulation employs a time-series power flow analysis to evaluate key electrical parameters such as voltage levels, line losses, and system stability. This approach enables the assessment of the proposed smoothing method under different solar irradiance and load scenarios. The impact of Alpha-Beta filter-based smoothing is quantified by comparing bus voltage profiles before and after its implementation.

By modeling the distribution system under high PV penetration conditions, the simulation framework provides a realistic testbed to evaluate the interactions between solar generation, energy storage, and grid dynamics. Critical nodes with high sensitivity to PV fluctuations can be identified for further analysis or control optimization.

B. *Developing the PV Smoothing Method*

To mitigate short-term fluctuations in PV output, a smoothing algorithm based on the Alpha-Beta filter is developed and implemented in Python. The Alpha-Beta filter is selected for its low computational complexity and capability for real-time prediction. It estimates the next-second PV output using previous measurements and adapts BESS operation to compensate for deviations. The algorithm performs the following key functions:

- Predicts PV output in the immediate future based on observed trends.
- Calculates the required charging or discharging action to smooth the net output.
- Maintains PV output within a predefined variability threshold to avoid disturbances in voltage and frequency.

The Python-based implementation allows for flexibility in tuning Alpha and Beta parameters, enabling adaptability to various grid conditions.

C. Analyzing Different Simulation Scenarios

To thoroughly assess the performance and feasibility of the proposed PV smoothing method, multiple simulation scenarios are considered. These scenarios account for various environmental conditions, load variations, and PV penetration levels, which are critical for evaluating the algorithm's effectiveness across a broad range of operational states. In this study, we specifically analyze the impact of:

- Different smoothing factors (λ) to determine their influence on PV power fluctuation mitigation.
- BESS performance and State of Charge (SOC) to evaluate the efficiency of charge-discharge cycles and their effects on battery lifespan.
- Voltage variations before and after applying the smoothing method to assess its impact on grid stability.

By systematically examining these scenarios, this study provides a comprehensive evaluation of the effectiveness, adaptability, and overall impact of the proposed PV smoothing technique in high-PV penetration microgrids.

III. MATHEMATICAL MODEL OF THE ALPHA-BETA FILTER

The Alpha-Beta filter, known for its simplicity and computational efficiency, uses two tunable parameters: Alpha (α) and Beta (β). When calibrated according to the sampling interval, the Alpha-Beta filter can be transformed into a steady-state Kalman filter [16]. The governing equations are as follows:

$$\lambda = \frac{\sigma_w T^2}{\sigma_v}, \qquad (1)$$

$$\alpha = \frac{1}{8}(-\lambda^2 - 8\lambda + (\lambda + 4)\sqrt{\lambda^2 + 8\lambda}), \qquad (2)$$

$$\beta = \frac{\alpha^2}{2-\alpha}. \qquad (3)$$

Subject to the constraints:

$0 < \alpha < 1$, $0 < \beta < 2$, and $0 < 4 - 2\alpha - \beta$.

Where the smoothing factor λ also known as the tuning gain, is commonly used to balance process noise and measurement noise in estimation filters. The σ_w is the standard deviation of process noise, representing how much the system state (e.g., PV power output) changes due to natural fluctuations such as weather or solar irradiance. The σ_v is the standard deviation of measurement noise, indicating the uncertainty or error in sensor readings or observed PV values. And T is the time step between consecutive measurements (in seconds). This λ equation is critical in balancing prediction and correction within the Alpha-Beta filter, guiding how aggressively the filter responds to observed deviations. Besides, the values of α and β determine the filter's behavior and are derived from λ. They govern the trade-off between response speed and noise filtering:

- Higher values of α and β result in faster dynamic response, but at the cost of higher noise sensitivity.
- Lower values of α and β produce smoother results, but the response to sudden power fluctuations is slower.

The discrepancy between the predicted and actual PV power output determines the amount of compensation needed from the BESS. If the discrepancy is positive, the BESS discharges power to compensate for the shortfall. Otherwise, if the discrepancy is negative, the BESS charges to store excess power.

The Alpha-Beta filter estimates the future PV power output by using a predict-update mechanism based on the last known values and the error observed. The filtering steps are described as follows.

In prediction step:

$$X_k = X_{k-1} + \Delta T V_{k-1}, \qquad (4)$$

where X_k predicted PV output at time step k; V_{k-1} predicted velocity (rate of change of PV output) at time step *k-1*; ΔT is the time interval between updates (sampling period). In this study, V is assumed to be approximately constant over short intervals:

$$V_k = V_{k-1}, \qquad (5)$$

The residual error is calculated as:

$$\gamma_k = X_k - X_k, \qquad (6)$$

where X_k is the actual PV power measurement at time step k, and γ_k is the residual error between measured and predicted value. The estimated values are then updated using α and β by (7) and (8).

$$X_k = X_k + (\alpha\gamma_k) \qquad (7)$$

$$V_k = V_k + (\beta / \Delta T)\gamma_k \qquad (8)$$

The α and β are the filter gains tuned based on the noise characteristics. These equations correct both the predicted value and its rate of change based on the error.

The difference between predicted and actual PV output, γ_k, determines how the BESS responds:

- If γ_k >0: PV underperforms, and BESS discharges to compensate;
- Otherwise, If γ_k <0: PV overperforms, and BESS charges to store excess power.

This allows real-time correction with reduced unnecessary cycling, thereby enhancing BESS lifespan. The algorithm flowchart is depicted in Fig. 3.

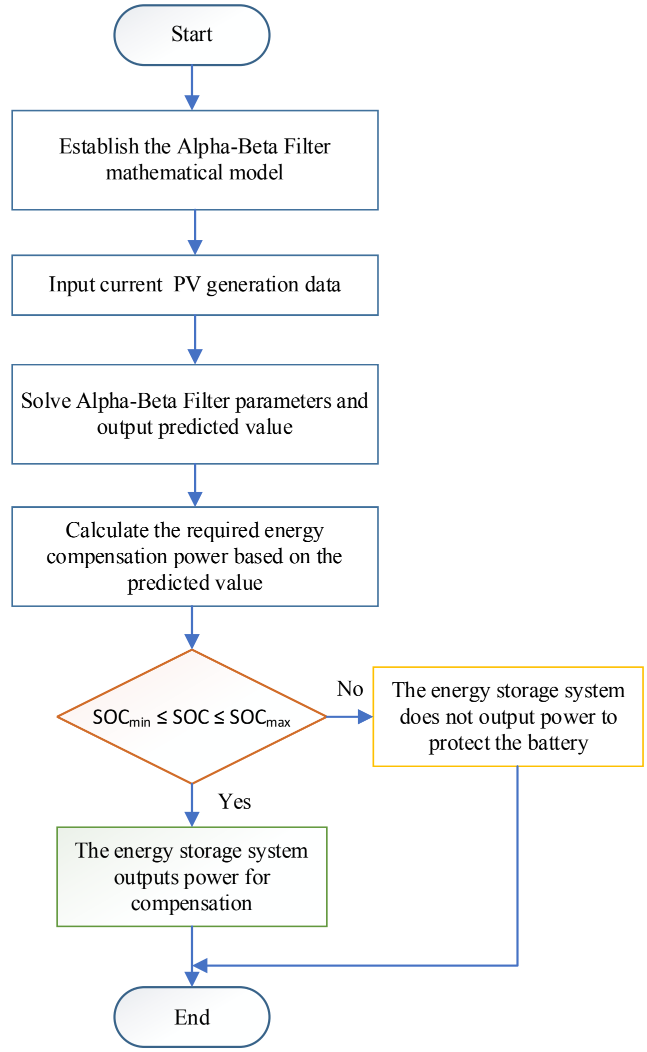


Figure 3. The algorithm flowchart

IV. SIMULATION AND EVALUATION

A. Description of the Simulation Scenario

In this study, the simulation analysis is conducted using existing electricity meter data from the campus microgrid on a partly cloudy day. The simulation assumes that the PV power output fluctuates significantly on that day. The historical load data is given as hourly averages, while the PV output power is recorded per second.

Fig. 4 and 5 illustrate the load and PV power output for the given day. This month corresponds to the peak electricity consumption period for the university. The peak load of microgrid#1 (Load 1) was approximately 61 kW, while themicrogrid#2 (Load 2) had a peak load of around 37 kW. The maximum PV power output reached 34 kW, and at that moment, the total load was approximately 83 kW. The PV penetration rate at that time was 38.55% (PV output power / total load power). On other off-peak days, the penetration rate was even higher, indicating a high PV penetration grid.

B. PV Smoothing Scenarios

The PV smoothing method proposed in this study utilizes the Alpha-Beta filter smoothing approach, implemented through a Python-based program. To determine the optimal smoothing effect, several PV smoothing scenarios were designed and tested. There are five scenarios in this study, where the key variable is the factor λ, as defined in (1). This factor influences the values of Alpha (α) and Beta (β), which in turn affect the smoothing performance. A total of five different PV smoothing scenarios were considered.

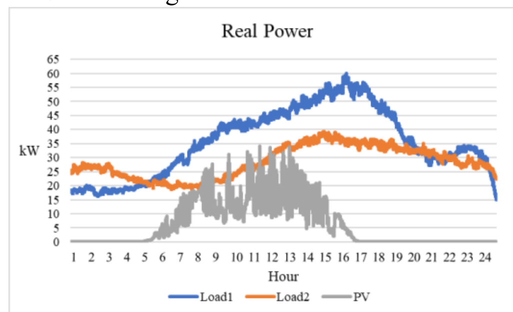


Figure 4. Load and PV power output on partly cloudy day

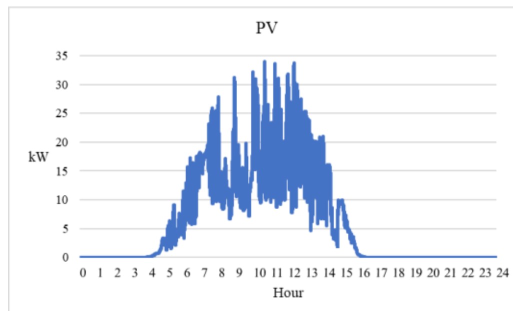


Figure 5. PV Power Output

C. Analysis of Results

The Alpha-Beta filter smoothing method is applied to process real-time PV output data. It predicts the next-second PV power output, determining the required charging and discharging energy of the BESS.

The proposed PV smoothing study is implemented using Python, based on the scenarios described in Section 4.2. The key outputs obtained from the simulation include:

- Raw-PV: Original PV power output.
- Smoothed-PV: PV power output after smoothing.
- Storage-BESS: Charging and discharging power of the battery energy storage system.
- PV variation (%): Original PV power variation per minute.
- PV smoothed variation (%): Smoothed PV power variation per minute.

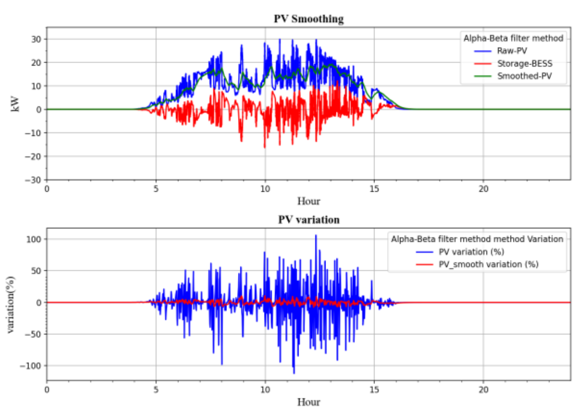
The simulation results are displayed in Fig. 6, which clearly demonstrate the differences between the original PV power output and the smoothed PV power output obtained using the proposed method with different factors.

In this study, the original PV power variation rate is 37.44%. Table I summarizes the key parameters for each simulation scenario, including: battery charging/discharging energy (kWh), number of charge and discharge cycles, SOC, and smoothed PV power variation rate, which representing the maximum fluctuation rate of PV output after applying the proposed smoothing method. The results demonstrate the effectiveness of the proposed approach in reducing PV power fluctuations, thereby improving grid stability, and optimizing battery energy storage operation.

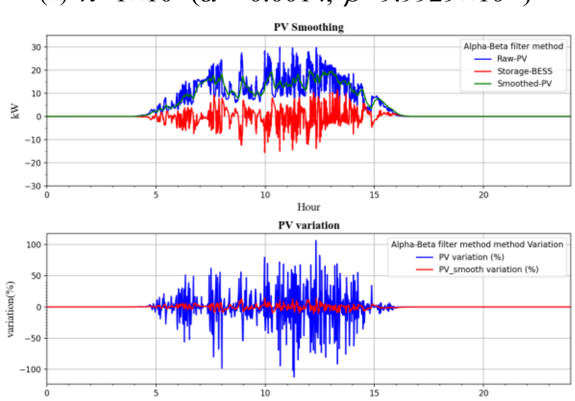
This section presents the simulation results obtained using the proposed PV smoothing method. As shown in Table I, the Factor λ of 1×10^{-6} demonstrated the most effective smoothing performance, achieving a maximum power variation rate of 3.11%. Additionally, all five data samples complied with the regulatory requirement of keeping power variation below 10% per minute. Given the variations in charging/discharging cycles, energy capacity, and battery storage limitations, the parameter λ can be adjusted accordingly to optimize the trade-off between smoothing effectiveness and battery lifespan extension.

In addition to meeting the power variation rate regulation, the study also evaluates voltage variation, as shown in Fig. 7. Fig. 8 illustrates the voltage fluctuation in the distribution network under two conditions: (1) With PV integration only; (2) With both PV integration and the BESS. The results indicate that in both cases, the voltage variation remains within the limit of 3%. The voltage variation rate is calculated using (8), ensuring compliance with grid stability requirements.

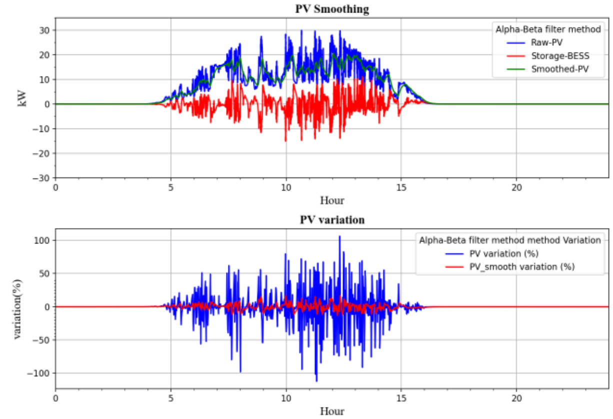
$$\Delta V(\%) = \frac{V_{pv} - V_{original}}{V_{original}} \times 100\% \tag{9}$$



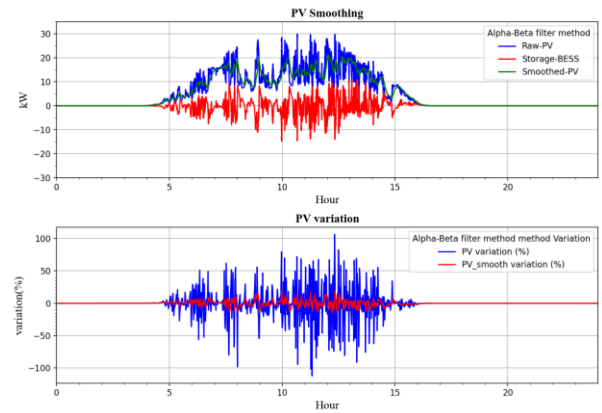
(a) $\lambda=1\times10^{-6}\,(\alpha=0.0014,\ \beta=9.9929\times10^{-6})$



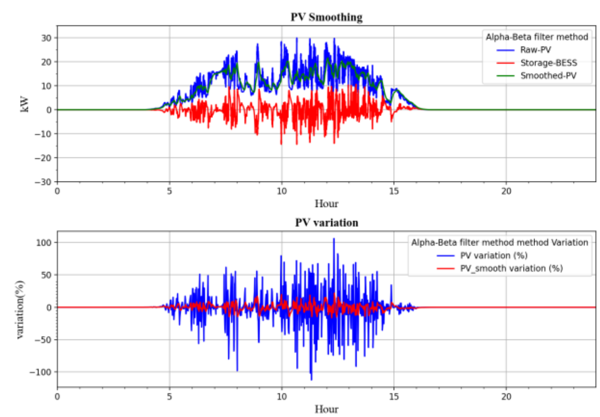
(b) $\lambda=2\times10^{-6}\,(\alpha=0.0019,\ \beta=1.9980\times10^{-6})$



(c) $\lambda=3\times10^{-6}\,(\alpha=0.0024,\ \beta=2.9963\times10^{-6})$



(d) $\lambda=4\times10^{-6}\,(\alpha=0.0028,\ \beta=3.9943\times10^{-6})$



(e) $\lambda=5\times10^{-6}\,(\alpha=0.0031,\ \beta=4.9921\times10^{-6})$

Figure 6. Simulation results with different factors

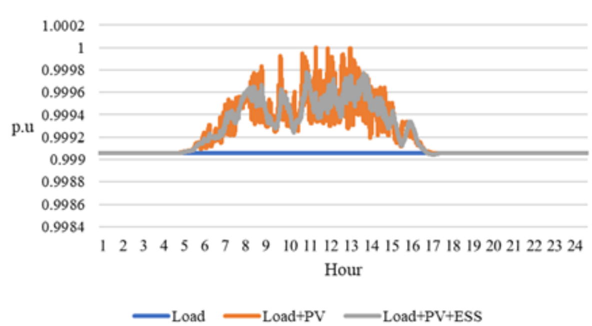


Figure 7. The daily voltage profile

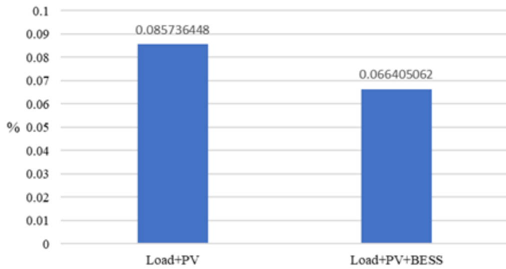


Figure 8. Voltage variation rate

TABLE I. SIMULATION RESULTS OF EACH FACTOR

Factor λ	1×10^{-6}	2×10^{-6}	3×10^{-6}	4×10^{-6}	5×10^{-6}
Charge (kWh)	16.46	15.32	14.64	14.13	13.73
Discharge (kWh)	17.11	15.81	15.05	14.49	14.05
Charge Cycles	20054	19662	19474	19309	19240
Discharge Cycles	22945	23337	23525	23690	23759
Avg. SOC (%)	50.41	50.93	51.20	51.38	51.51
Original Variation (%)	37.44	37.44	37.44	37.44	37.44
Smoothed Variation (%)	3.11	4.11	4.94	5.77	6.49

V. CONCLUSION

This study proposes an Alpha-Beta filter-based PV smoothing method, implemented using Python and simulated using OpenDSS. The method effectively reduces PV power variation, evaluates battery SOC, and calculate voltage variation while ensuring compliance with power fluctuation regulations. Simulation results demonstrate that the original PV power variation rate was 37.44%, which was significantly reduced using the proposed smoothing method. Among the five tested scenarios, the factor of $\lambda=1\times10^{-6}$ ($\alpha = 0.0014$, $\beta=9.9929\times10^{-6}$) yielded the best performance, achieving a smoothed PV power variation rate of 3.11%, representing a 91.7% reduction compared to the original variation. Overall, the proposed Alpha-Beta filter-based PV smoothing method successfully reduces power fluctuations by over 90%, optimizes BESS operation, and ensures grid stability while maintaining efficient energy storage utilization. These findings validate the feasibility and effectiveness of the method for microgrids with high renewable energy integration, making it a promising solution for enhancing the stability of high-PV penetration grids.

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