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A New Adaptive Strategy for Enhancing the Stability of Isolated Grids through the Integration of Renewable Energy and V2G Management

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Abstract: The integration of renewable energy sources into isolated microgrids introduces significant power fluctuations due to their intermittent nature. This study addresses the need for advanced power smoothing methods to enhance the stability of isolated networks. An innovative adaptive strategy is presented, combining photovoltaic solar generation with vehicle-to-grid technology, utilizing an enhanced adaptive moving average filter with fuzzy logic control. The primary objective is to dynamically optimize the time frame of the Li-ion battery energy storage system for immediate power stabilization, leveraging the high energy density and rapid response capabilities inherent in electric vehicle batteries. The methodology encompasses data acquisition from photovoltaic panels, definition of fuzzy logic control rules, and implementation of the proposed method within a computer-controlled system connected to a bidirectional three-phase inverter. Experimental results highlight the proposed method's superiority over conventional moving averages and ramp-rate filters.

Keywords: renewable energy integration; electric vehicle batteries; power smoothing techniques; vehicle-to-grid; low-inertia power systems

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1. Introduction

The current literature extensively examines the reduction of fluctuations in the electrical grid caused by the intermittent behavior of renewable sources [1–4]. For instance, studies such as [5] have evaluated spline-based control methods for smoothing photovoltaic (PV) power, demonstrating that effective smoothing effects can reduce the required capacity of energy storage systems (ESS). Additionally, advanced filters like the Savitzky-Golay (S-G) filter have shown significant improvements. Research such as [6] has compared moving average (MA) and low-pass filter methods. Another promising approach involves moving regression (MR) filters with state of charge (SoC) control. Studies like [7] have shown that the MR filter can reduce PV power variability without increasing ESS capacity, making it more effective than other methods, such as MA and median filters.

Improving energy quality is crucial in microgrids (MG) and isolated systems [8–11]. Research such as [12] has proposed smoothing methods using supercapacitor ESS. Studies like [13] have used smoothing techniques such as MA and ramp rate control to determine optimal battery capacity, providing empirical models for project feasibility assessment. The application of MA filters has also extended to wave energy conversion plants, as described in [14]. Research such as [15] uses enhanced optimization algorithms to tailor hybrid ESS to solar power variations, highlighting the effectiveness of adaptive control in energy management. Power ramp compensation is also essential in MG with high PV penetration. Studies like [16] have developed compensation strategies based on multilevel ESS, using ramp rate control methods to smooth solar power fluctuations and meet rapid load demands. Another promising approach to ensure network stability is using linear programming techniques with priorities. A recent study proposed a power management method based on linear programming for a multi-feeder ultra-fast DC charging station. This approach maximizes the efficiency of renewable resources, local storage solutions, and electric vehicles to minimize their grid impact while also observing charging priorities and power flow limitations. Simulation results confirm that this approach effectively enhances grid stability amidst significant fluctuations in load [17]. Furthermore, optimizing hybrid power generation plants, as in [18], has shown how the optimal combination of wind, solar, and ESS can reduce output fluctuations and enhance system reliability in grid-connected systems. Thus, energy quality is notably enhanced [19–21].

Implementing Fuzzy Logic Controller (FLC)-based energy management systems has been highlighted in the literature for its effectiveness in smoothing power profiles in electro-thermal MG. A recent study [22] designed an EMS using FLC to smooth the power profile in a residential MG. Using year-long measured data, they demonstrated an 11.4% reduction in peak network power absorption and a significant decrease in power profile ramp rates compared to previous studies. Study [23] proposed a system integrating a PV Battery Energy Storage System (BESS) with doubly fed induction generator systems, employing an FLC optimized by moth-inspired optimization algorithms to maximize active power and smooth power transfer to the grid converter. Combining fuzzy logic-based maximum power point tracking (MPPT) with active power management offers fast and accurate tracking, reducing output power fluctuations and improving system efficiency compared to classical methods, as demonstrated in [24,25]. Additionally, using FLC for MPPT and voltage compensation, authors in [26] demonstrated notable effectiveness in enhancing energy efficiency and power quality across various operational conditions.

Managing PV/diesel/BESS hybrid systems in isolated systems has been optimized using fuzzy logic-based power management systems (PMS) [27]. This study proposed an adaptive PMS using fuzzy logic to ensure smooth transitions between different operating modes, showing significant improvements in PV generator efficiency and system stability. In DC-bus MG, energy stability and quality have been improved using FLC-ESS [28]. This study investigated the use of superconducting magnetic energy storage (SMES) and battery systems controlled by FLC to mitigate voltage and power fluctuations, demonstrating improved stability and rapid response to climate and load variations. Finally, optimal regulation of energy flow in PV systems with BESS has been achieved using adaptive FLC [29,30], highlighting FLC robustness and smooth performance in DC-bus voltage regulation and efficient energy flow management among PV systems, BESS, and loads. Similarly, studies [31,32] demonstrate that fuzzy logic applied to improve the quality of renewable systems is promising.

The literature review reveals various studies focused on mitigating power fluctuations in electrical grids caused by intermittent renewable sources. Studies such as [5] have evaluated spline-based control methods and S-G filters for PV power smoothing, showing significant reductions in variability with minimal additional storage capacity. However, there is an opportunity to optimize these methods specifically for integration into vehicle-to-grid (V2G) systems in isolated networks, better adapting them to variable load and solar generation conditions [5,6]. Moreover, while lithium-ion batteries from electric vehicles (EVs) have been used to stabilize the grid, as seen in studies like [7], there is still room to maximize their responsiveness and efficiency in isolated MG. Solutions could improve charge/discharge management to optimize ESS, adapting to variable demand and generation patterns thereby enhancing V2G integration [7,12].

Furthermore, while methods like MA and ramp rate techniques for frequency control and power smoothing have been compared, as outlined in studies such as [13], a more detailed and comprehensive comparison of these strategies in specific MG environments could provide additional insights into their effectiveness and adaptability. This exploration would be crucial for optimizing energy management strategies in variable network and weather conditions [13,14]. Additionally, although results are validated in MG laboratories, as demonstrated in studies like [15], there is an urgent need to investigate how these results translate and validate in real operational scenarios outside the controlled laboratory environment. This approach would allow for more robust validation of proposed strategies and a deeper understanding of operational challenges in real networks and variable climate conditions [15,16]. Finally, while methods such as MA filters and fuzzy logic-based control for power smoothing and grid stability have been explored, specific studies have not adapted and optimized these techniques for simultaneous integration into V2G systems in isolated MG by adjusting the ramp rate in real time.

To overcome these challenges, this study presents an innovative adaptive strategy to improve the stability of isolated networks by integrating renewable PV generation and energy management using V2G technology (V2GSUN method). The original contribution of this study lies in implementing an adaptive strategy that integrates PV energy, energy management, and V2G technology to stabilize isolated networks using an enhanced adaptive MA filter with fuzzy logic. This allows lithium-ion batteries in EVs to act as dynamic units for ESS and supply, leveraging their high energy density and rapid response capabilities.

2. Methodology

Figure 1 provides a schematic overview of the methodology employed in this study. The input data collection phase initially involves gathering data, including real-time output power from PV panels observed in a laboratory setting throughout a typical day. Subsequently, the study introduces the V2GSUN method, which incorporates a Fuzzy Logic controller (FLC). The key goal of this control system is to optimize the time window size of the BESS to smooth out power fluctuations in real-time effectively.

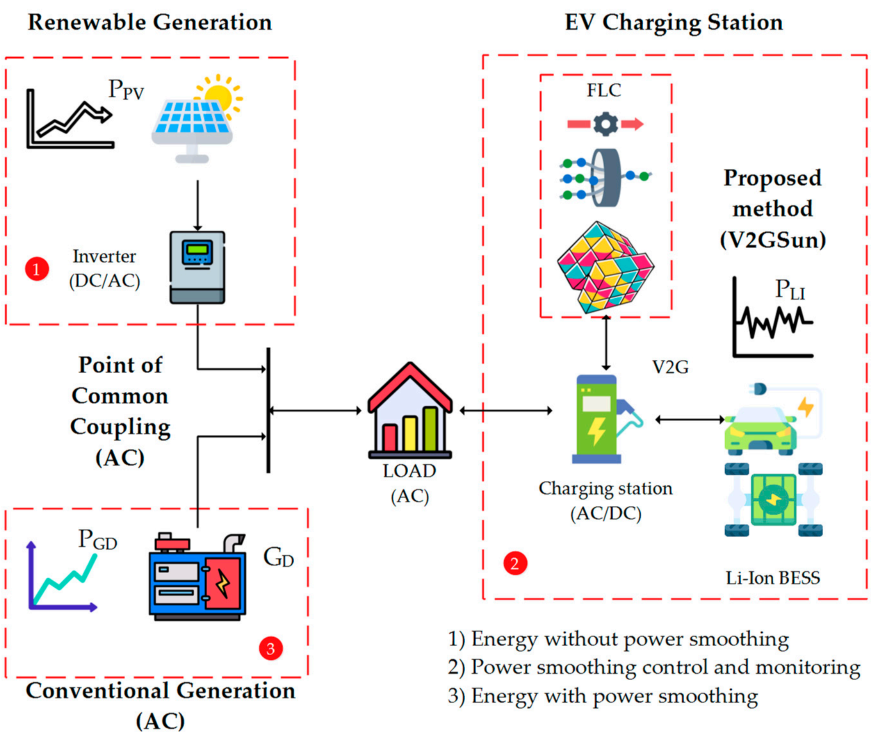

Figure 1. General scheme of the proposed methodology. Reproduced with permission from [33].

Under experimental conditions, the isolated power system is expected to experience significant frequency variations due to handling highly variable power from renewable generation. The operating procedures for grid networks are generally more lenient with island system frequency standards than bulk power systems. This is due to the operational complexity of such systems, especially when integrating renewable distributed energy resources.

To accomplish this objective, the experimental microgrid's data logger is used to monitor the supervisory control of the BESS. The proposed method's effectiveness is assessed in comparison to conventional techniques such as the MA and traditional ramp-rate (R-R) methods. For experimental testing purposes, a BESS is employed to replicate the battery characteristics of an EV, specifically a BYD T3 electric van available in the laboratory. This battery is known for its high energy storage density and capability to meet performance requirements effectively. The EV's BESS is integrated into the grid using a 50 kW bidirectional three-phase inverter, applying the proposed method within the computerized control system. The results obtained are rigorously validated through experiments under diverse technical criteria, supplemented by a detailed analysis of variability and energy dynamics. This comprehensive assessment underscores the reliability and practicality of the proposed methodology in real-world applications.

2.1. Advancement of a Power Smoothing Methodology Using MA for Energy Applications

The MA method employs statistical techniques rooted in time series analysis. The fundamental concept of the V2GSUN algorithm involves averaging a series of data points. The equation below illustrates the MA filter applied in this study [12].

$$P_{PVC}[k] = \left(\frac{1}{N}\right)(P_{PV}[k] + P_{PV}[k-1] + \ldots + P_{PV}[k-N+1]) \quad (1)$$

Here,

- P_{PV} denotes the PV output power;
- P_{PVC} signifies the power output smoothed via the MA method;
- N denotes the count of samples contained within the time frame;
- k serves as the iteration index.

Upon completing a predetermined iteration, the P_{PV} is updated with the smoothed power P_{PVC} of the PV system. The discrepancy between the smoothed and input powers referred to as P_{SC}, is directed to the BESS power controller to compensate for the PV-generated power delivered to the grid.

2.2. New Control Methodology

The control strategy proposed in this study is applied within a Li-Ion BESS connected to the Point of Common Coupling (PCC) through a bidirectional power inverter. This inverter facilitates precise control over the injection and absorption of active and reactive power into the grid. Controlled conditions have been established to evaluate the efficacy of this approach.

The V2GSUN method fundamentally relies on the MA approach, enhanced through FLC. This method utilizes input parameters such as photovoltaic solar power and the grid generator frequency to make informed decisions. The implementation of the V2GSUN method involves several key steps.

First, data collection is essential, where real-time information on PV solar power generation and grid generator frequency is obtained. Next, fuzzy logic integration is employed to process these input parameters, guided by fuzzy rules. This integration helps to refine the data window for the output time, ensuring effective smoothing of power injections into the grid. The system is connected to a fixed load and an EV, where the EV's batteries play a critical role in mitigating power peaks caused by solar irradiation while maintaining an optimal state of charge.

The optimization of the V2GSUN method focuses on refining the parameters used within the fuzzy logic framework to improve decision-making efficiency. This involves adjusting input parameters to enhance the system's responsiveness and regularly updating the fuzzy rules based on system performance and real-time data analysis. To illustrate the effectiveness of the V2GSUN method, it was applied in a scenario where it managed power injections from a grid-connected PV solar system.

An off-grid diesel generator is incorporated into a bus bar system, operating as a three-phase voltage source that provides frequency and voltage references for an isolated grid. This isolated bus bar includes an inverter linked with PV energy systems and emulates an EV-BESS. The main goal is to reduce fluctuations in PV power and enhance grid frequency stability, achieved through the energy buffering capacity of the Li-Ion BESS.

Innovatively, the strategy enhances the MA method's effectiveness by incorporating an FLC. The FLC acts as a dynamic control system that adjusts the time window of the MA power based on input parameters such as energy input, PV power, and the SoC of the BESS. The FLC's output offers a variable power change rate over time, providing adaptability during periods of high loads and limited resources. The diagram of the new controller is shown in Figure 2.

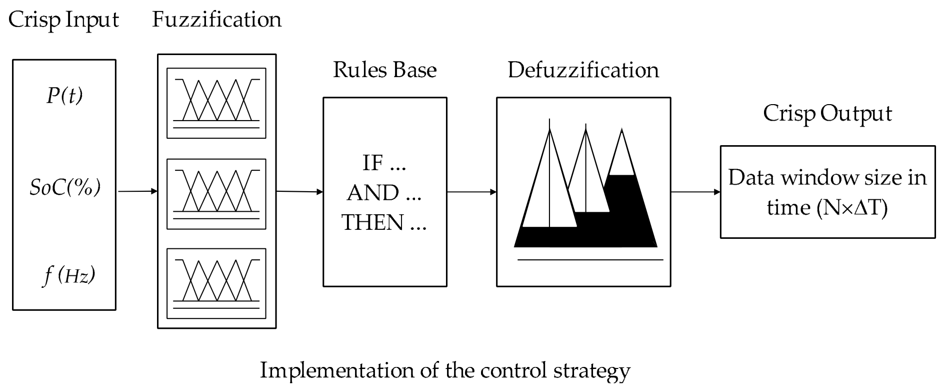

Figure 2. Schematic diagram of the proposed Fuzzy Logic Controller. Reproduced with permission from [33].

The algorithm samples injected active power, PV power, BESS SoC, and grid frequency from the diesel generator at a time interval ΔT. Pre-established fuzzy rules are applied to make determinations that directly impact the duration of the time window $N \times \Delta T$, modifying it to suit the immediate requirements for smoothing power in real time. As a result, the resulting output is shaped by the current status of input parameters such as PT, SoC, and system frequency.

The time window size, $WS = N\Delta T$, is dynamically adjusted using fuzzy logic to optimize the SoC of the Li-Ion BESS in real time. Control rules for the proposed strategy are detailed in Table 1, outlining different levels of smoothing (HS = high smoothing, S = smoothing, MS = moderate smoothing, LS = low smoothing, NS = no smoothing) categorized VH (very high), H (high), M (medium), L (low) and VL (very low). Membership functions designed for this approach are depicted in Figure 3. These functions adapt the data window size based on real-time power, frequency, and BESS SoC changes. Triangular and trapezoidal membership functions are utilized, with defuzzification employing the centroid method.

It is worth noting that, in the case of the Ecuadorian electrical utility used for the experimental tests, the nominal frequency is 60 Hz, with slight variations of ± 0.15 Hz (0.25%) during normal operation. However, the frequency tolerance for the Ecuadorian insular grid is more lenient due to the significant challenges associated with managing massively integrated renewable resources in a low-inertia power system. This scenario has necessitated the exploration of solutions like the one proposed in this study.

Table 1. FLC rules for power concerning the SoC of the BESS and grid frequency.

		VH	H	M	VL	L
SoC [%]	M	MS	S	S	MS	S
	VL	VHS	HS	MS	NS	S
	VH	VHS	VHS	MS	VHS	HS
	H	MS	HS	S	HS	MS
	L	HS	MS	S	S	NS
Frequency [Hz]	VH	VHS	VHS	MS	VHS	HS
	H	MS	HS	S	HS	MS
	M	MS	S	S	MS	S
	VL	VHS	HS	MS	NS	S
	L	HS	MS	S	S	NS

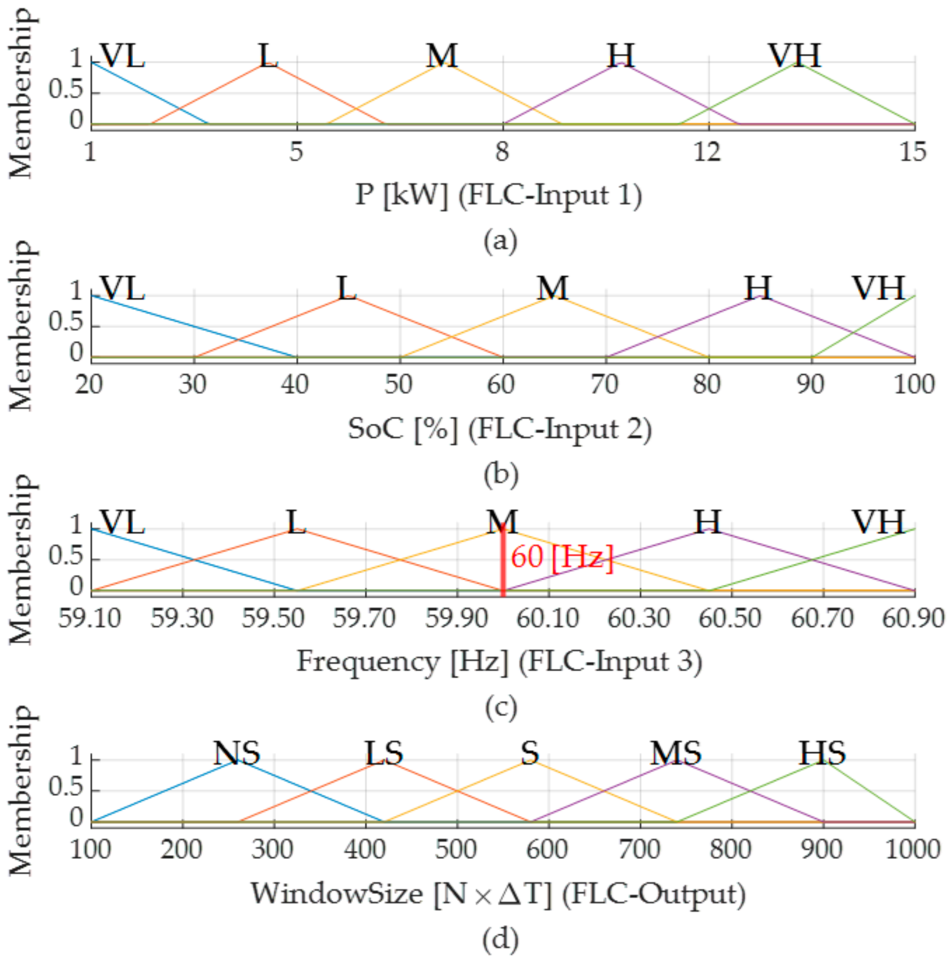

Figure 3. Proposed FLC membership functions for power smoothing control: (**a**) Input 1: Power (P), (**b**) Input 2: SoC, (**c**) Frequency, and (**d**) Output: data time window size (WS). Categories include NS (no smoothing), LS (low smoothing), S (smoothing), MS (moderate smoothing), and HS (high smoothing). Input 1 values are represented as VL (very low), L (low), M (medium), H (high), and VH (very high). Input 2 values denote percentages: very low = 10%, low = 30%, medium = 50%, high = 70%, and very high = 90%. Reproduced with permission from [33].

To be conservative, a broad frequency variation margin was considered when defining the numerical values for the membership function illustrated in Figure 3c, set at ±1.5%. This selection is tailored specifically for this system; nevertheless, it is crucial to highlight that the actual system's conditions where this solution is to be implemented should be taken into account to adjust this threshold appropriately.

The membership function's chosen frequency values at VL (Very Low) and VH (Very High) reflect this broader margin to accommodate potential fluctuations. These values are not necessarily the maximum standard frequency tolerances set by the electricity provider but are rather selected to ensure robustness in the face of variable operating conditions.

The FLC rules define the relationship between power (P), frequency (f), and the SoC, determining the time window size (WS). This ensures that the smoothing process adapts to the current conditions of the PV system and the Li-Ion BESS, maintaining optimal power smoothing and grid stability. Figure 4 illustrates the changes in the three inputs and the output during FLC evaluation. The surface is obtained by defuzzifying the tabulated membership functions using the centroid method, which calculates the output by finding the center of the area under the curve of the aggregated fuzzy set. This method provides a precise control action and is ideal for applications requiring fine-tuned and responsive control, such as the proposed power smoothing technique.

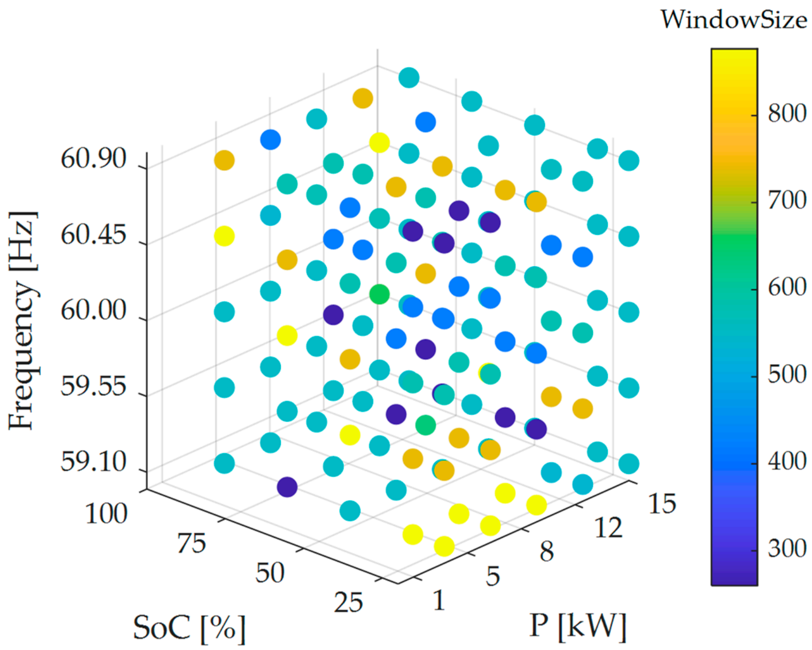

Figure 4. Graphical representation depicting the inputs and output generated by the newly developed FLC.

3. Study on Real-Time Testing of an Isolated Microgrid

3.1. Test Bench for the Experimental Implementation

This study employed MATLAB algorithms to perform real-time tests on an isolated MG at the University of Cuenca's Micro-Grid Laboratory in Ecuador [34]. The MG setup includes 15 kWp polycrystalline PV panels and a 44 kWh lithium-ion BESS. Figure 5 illustrates the configuration, which comprises solar panels (P_{PV}), a thermal diesel generator (GD) with delivered power (P_{GD}), a three-phase programmable load, and an electric vehicle charging station (EVCS) featuring a BYD electric vehicle (EV). A constant 20 kW load was applied to the programmable load to maintain system power balance, ensuring laboratory conditions where power fluctuations originate solely from intermittent PV injection. This method effectively manages the possibility of reverse power flow to the diesel generator when there is excess renewable energy, thus maintaining the safe and consistent operation of the test bench.

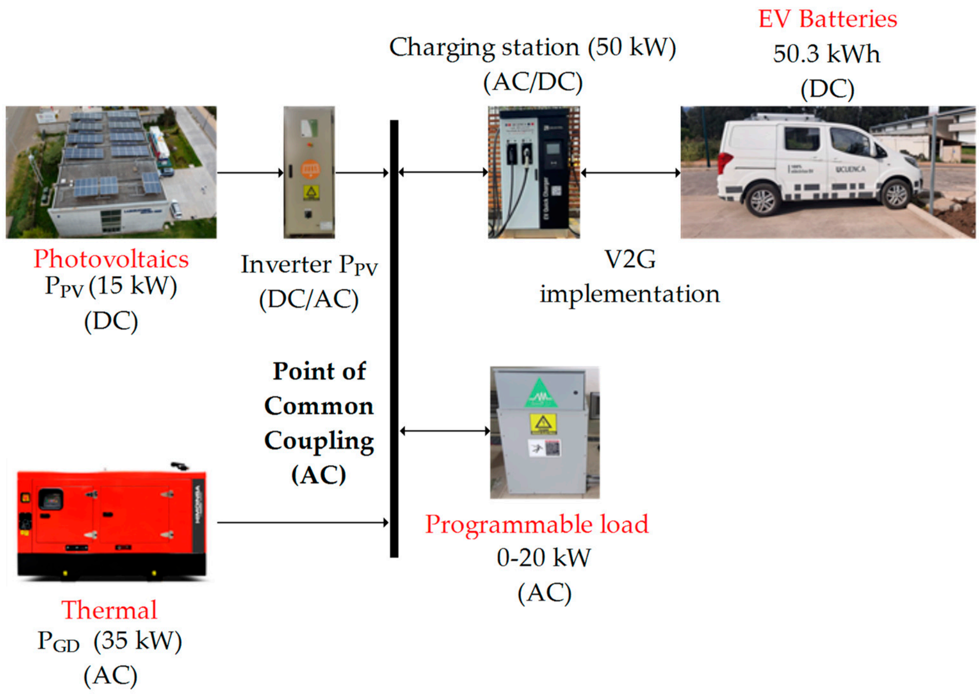

Figure 5. Test bench implemented in the laboratory. Reproduced with permission from [33].

The laboratory includes a BYD T3 van featuring a 300 kW power output and a 100 kW electric motor, specifically the BYD-1814TZ-XS-B35KW model. The LiNIMnCo battery boasts a 50.3 kWh capacity and functions at a combined voltage of 438 VDC. It is structured with 12 modules housing 120 cells and includes a CCS2-type connector. For V2G emulation in a controlled experimental environment, a lithium-ion battery bank consisting of 11 cells with a voltage output of 642 VDC and a capacity of 44 kWh (Samsung model ELPT392-0002) was utilized. This setup is linked to a 50 kW power converter engineered to simulate a bidirectional charger, enabling the BESS to inject energy back into the grid. The setup supports G2V and V2G operation modes, facilitating efficient energy management and peak demand control. This precise control and testing environment provides a robust platform for validating V2G strategies. It allows emulation of various operational scenarios and accurate power flow management to evaluate system performance comprehensively. This evaluation is essential for demonstrating the practical feasibility of V2G concepts in isolated MG setups, showcasing benefits such as enhanced grid stability, increased renewable energy integration, and efficient ESS utilization.

3.2. Practical Implementation of the Proposal

The pseudo-code in Algorithm 1 illustrates a ramp rate control process in a power system using fuzzy logic, incorporating generator frequency as an input. Initially, devices are connected via Modbus to read initial values. A Fuzzy Inference System (FIS) is then defined with three input variables: state of charge of the supercapacitor (SC_{SOC}), photovoltaic power (P_{PV}), and generator frequency ($Frequency$). An output variable for the desired time window size (WS) is established, and triangular membership functions (trimf) are configured for these variables. Subsequently, fuzzy rules are added to the FIS to determine the data window size (Algorithm 2) based on the inputs. During real-time processing, a continuous loop at regular intervals of 100 ms reads current values from the Modbus devices, applies the FIS to determine the desired data window size (WS), and uses a moving average method to smooth the power output. Finally, the compensated power values (P_{PVC}) are written back to the Modbus device, and the SC_{SOC} state of charge is monitored, repeating this process indefinitely to ensure efficient and real-time power control.

Algorithm 1: Pseudo-code for implementing the V2GSUN method

Input:
SC_{SOC}, P_{PV}, $Frequency$
Membership functions for SC_{SOC}, P_{PV}, $Frequency$
Fuzzy rules
Sampling time t
Initial window: WindowSize (WS)
Output:
window: WindowSize (WS)
Process:
Initialization:
Connect to Modbus devices at IP and port.
Read initial values from SC_{SOC}, P_{PV} and $Frequency$ system.
Define Fuzzy Logic System:
input variables (P_{PV}) with ranges [0–15].
input variables (SC_{SOC}) with ranges [0–100].
input variables ($Frequency$) with ranges [59.1–60.9].
output variable output variable (WS) with range [100–1000].
membership functions for P_{PV}, SC_{SOC}, $Frequency$
fuzzy rules for decision-making [P_{PV}, SC_{SOC}, $Frequency$].

Real-time Data Processing (loop indefinitely):
Measure elapsed time (t = 100 [ms])
Read current SC_{SOC}, P_{PV} and $Frequency$ from Modbus.
Inputs = [SC_{SOC}, P_{PV}, $Frequency$]
WS = evalfis(inputs, fis)
window = WS
$P_{PVC} = PS(P_{PV}, WS)$
Update Modbus with new power values (P_{PVC}).

End
End

Algorithm 2: Pseudo-code for implementing the *WS* feature

$PS(P_{PV}, ma, WS)$
Add new sample P_{PV} to moving average vector ma.
Adjust length of vector ma to match WS.
Calculate moving average (P_{PV}) of V2GSUN.

The main flowchart (see Figure 6) describes the implementation of the proposed method. This algorithm begins by connecting to the Modbus system via TCP/IP. Initial data, including P_{PV}, *Frequency*, *SoC*, and *WS*, are input. These data are read and processed in a loop, with an index (*i*) incrementing in each iteration.

In each cycle, the algorithm applies a power smoothing (*PS*) technique to the input data to obtain compensated photovoltaic power (P_{PVC}). This smoothing technique considers the moving window size (*WS*), allowing the system's response to adjust according to the PV production and demand variability. The loop continues iterating until a specific stop condition is met, indicated by a decision block with the instruction "break".

The flowchart breaks down the subroutine $PS(P_{PV}, ma, WS)$, which calculates the moving average of the PV power data (*ma*). If the current length of the moving average exceeds the window size (*WS*), the moving average is adjusted by removing the oldest data and adding the new PV power data (P_{PV}). Finally, the average of the compensated PV power (P_{PVC}) is calculated to smooth the power output and enhance system stability.

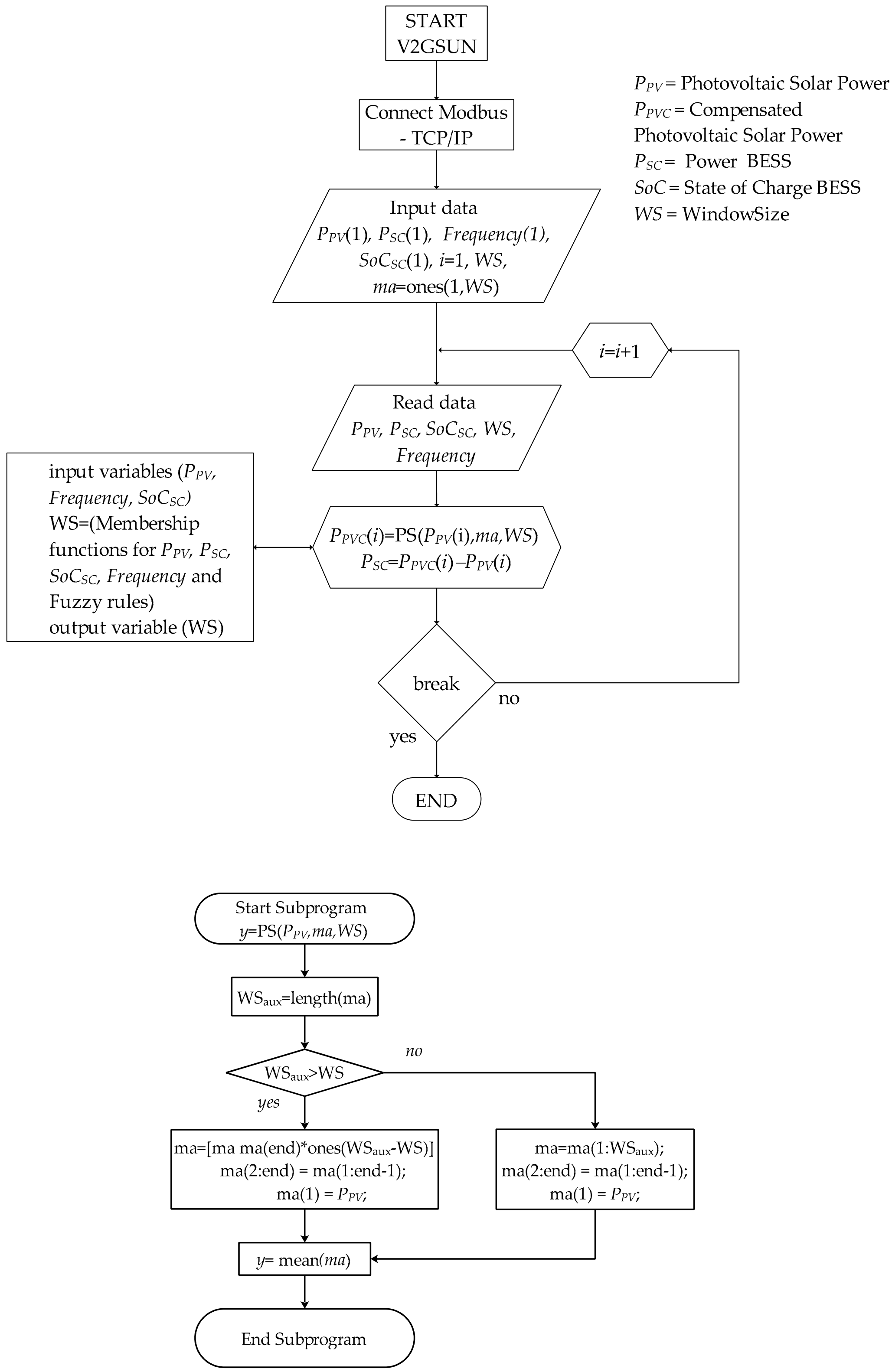

Figure 6. Flowchart for the implementation of the V2GSUN power smoothing method.

3.3. Case Base Implementation under Actual Laboratory Conditions

The variability in daily PV generation profoundly impacts isolated system operations and the design of BESS or management systems. Analyzing the daily solar energy production curve with high and low fluctuations is crucial for optimizing PV equipment to suit specific project conditions. For emulation purposes, a power curve (P_{PV}) selected for this study (see Figure 6, highlighted in red) exhibits significant variability influenced by weather, location, and system characteristics. Figure 7 depicts the daily power curve based on actual measurements from the Micro-Grid Laboratory in Cuenca, Ecuador (geographical coordinates: −2.891918819933002, −79.03857439068271). Choosing a highly variable generation profile is essential as it represents worst-case conditions for rigorously testing the V2G strategy and validating corrective actions. Managing grid stability and ESS efficiently under such variability poses substantial challenges, making it imperative to assess system response comprehensively under realistic conditions.

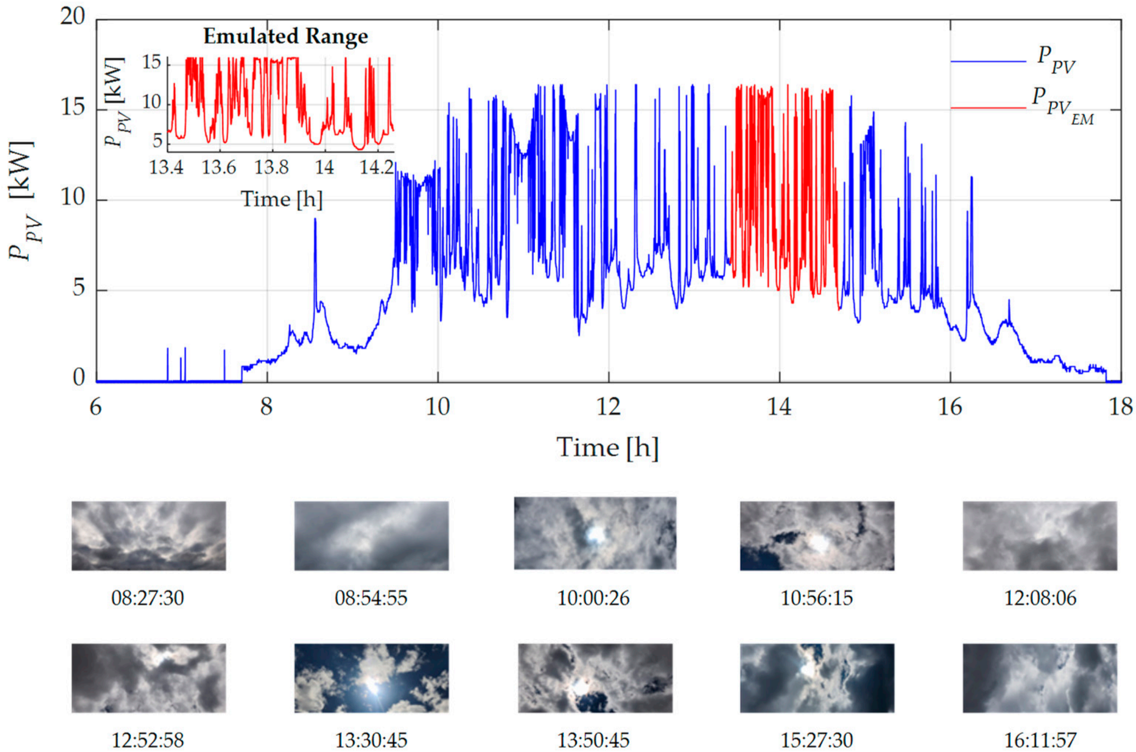

Figure 7. Typical power fluctuations in the daily PV production with a photographic record of the sun every hour during the day. Reproduced with permission from [33].

Figure 8 shows the results of applying one hour of high variability PV production in the test system. As expected, integrating a generation source with high variability (Figure 8a) forces the operational synchronous generation to compensate for such power imbalances (Figure 8b). Due to this case's severe power control requirements, the grid frequency varies substantially (Figure 8c). Additionally, the voltage of each phase at the PCC also experiences significant fluctuations, adversely affecting the power quality of the isolated system. This experiment demonstrates the need to mitigate the operational issues of high-variability PV power integration in weak and isolated power systems.

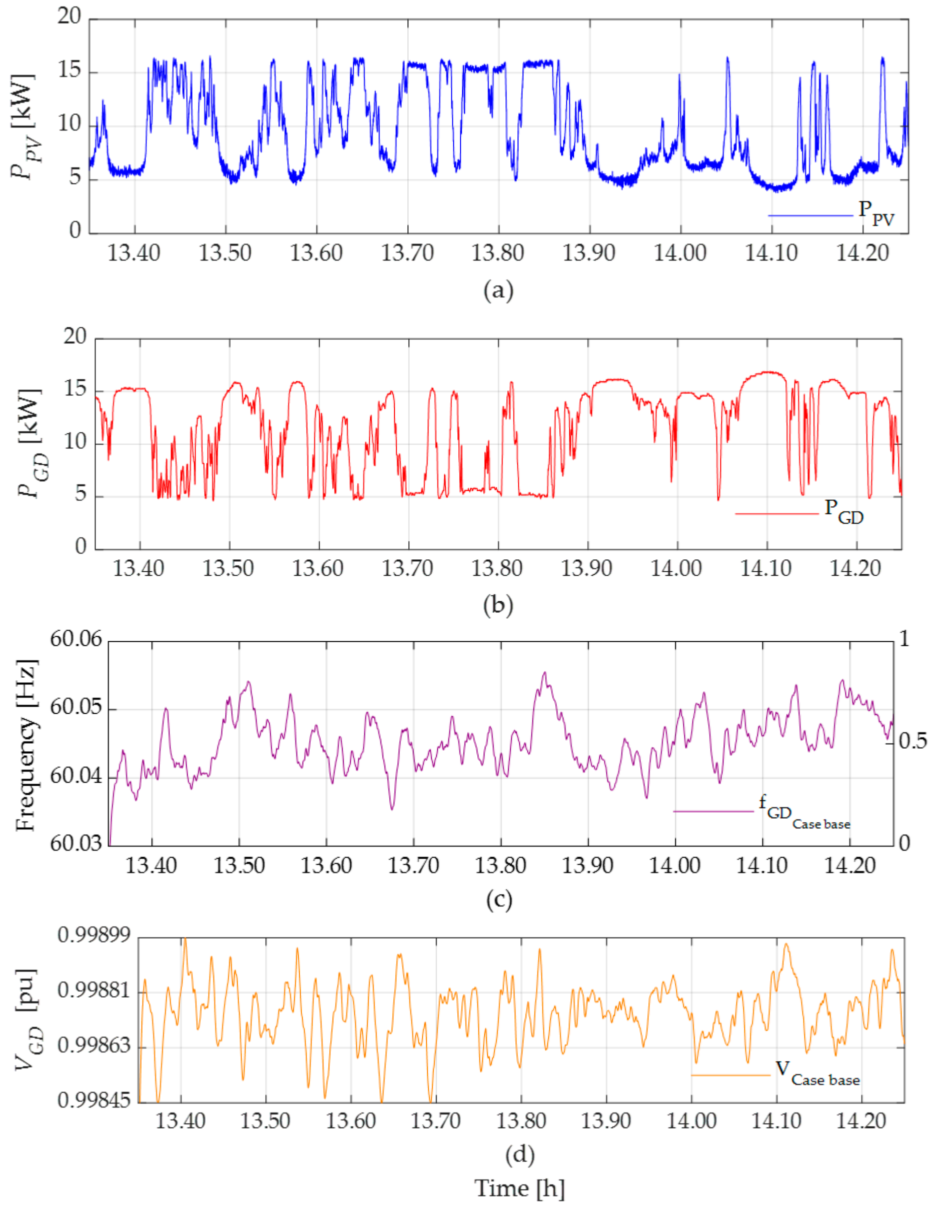

Figure 8. Power response results without using V2G, baseline case: (**a**) PV power, (**b**) GD power, (**c**) generator frequency, and (**d**) generator line voltages.

4. Data Analysis and Interpretation

This research investigated the implementation and performance of an advanced method for smoothing power fluctuations, specifically the Moving Average (MA) filter, by adjusting the data acquisition time window using an FLC. A comparative analysis was carried out with two popular power smoothing solutions previously tested by the authors in [12], the Ramp-Rate (R-R) and MA filters, to assess the effectiveness of the proposal. Two realistic scenarios comprise our research:

- **Study Scenario 1-Li-Ion Storage System with Moderate SoC level**: aimed to maintain the Li-Ion BESS's SoC within the range of 20% to 80% initially.
- **Study Scenario 2-Li-Ion Storage System with Low SoC level**: In this undercharging scenario, the Li-Ion BESS began with an SoC below 20%, prioritizing EV charging.

4.1. Study Scenario 1: Li-Ion Storage System with Moderate SoC Level

Figure 9 presents an overview of the experimental findings from the MA method, showing various power profiles: the renewable PV production (in blue colored line), the power response of BESS (in black line), and the compensated power delivered to the grid (in green colored line). The dynamic behavior of the thermal GD power is depicted in Figure 9a, emphasizing the MA method's effectiveness in stabilizing power fluctuations. Figure 9b demonstrates the improved smoothing of power output achieved by the MA method. Additionally, Figure 9c shows the enhanced frequency response of the GD, indicating improved stability, while Figure 9d illustrates the mitigated voltage fluctuations. These results underscore the MA method's effectiveness in enhancing both frequency and voltage responses, validating its utility in improving operational stability.

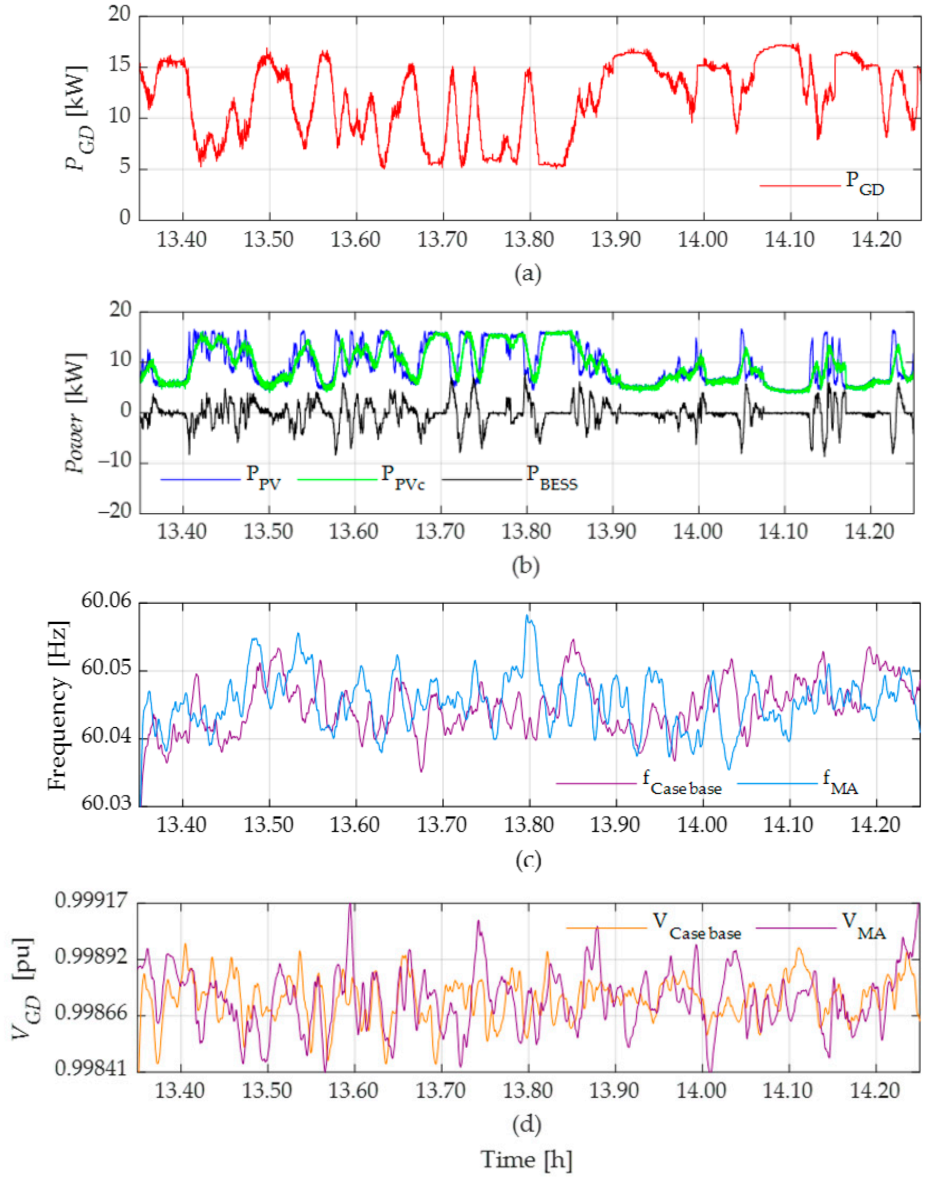

Figure 9. Results of implementing the MA method for V2G aimed at smoothing PV power: (**a**) GD power, (**b**) PV power compensated with Psc, (**c**) Generator frequency, and (**d**) generator line voltages.

The experimental outcomes of the RR method are depicted in Figure 10, showcasing various power profiles. Figure 10a displays the GD power response, highlighting the R-R method's relief in load tracking by the thermal unit. The effectiveness of power smoothing provided by the R-R method is evidenced in Figure 10b. Moreover, Figure 10c illustrates the improved frequency response of the GD, indicating enhanced stability, while Figure 10d presents the minimized voltage fluctuations at the GD. These findings emphasize how the

RR method contributes to optimizing both frequency and voltage responses, validating its application in enhancing system performance.

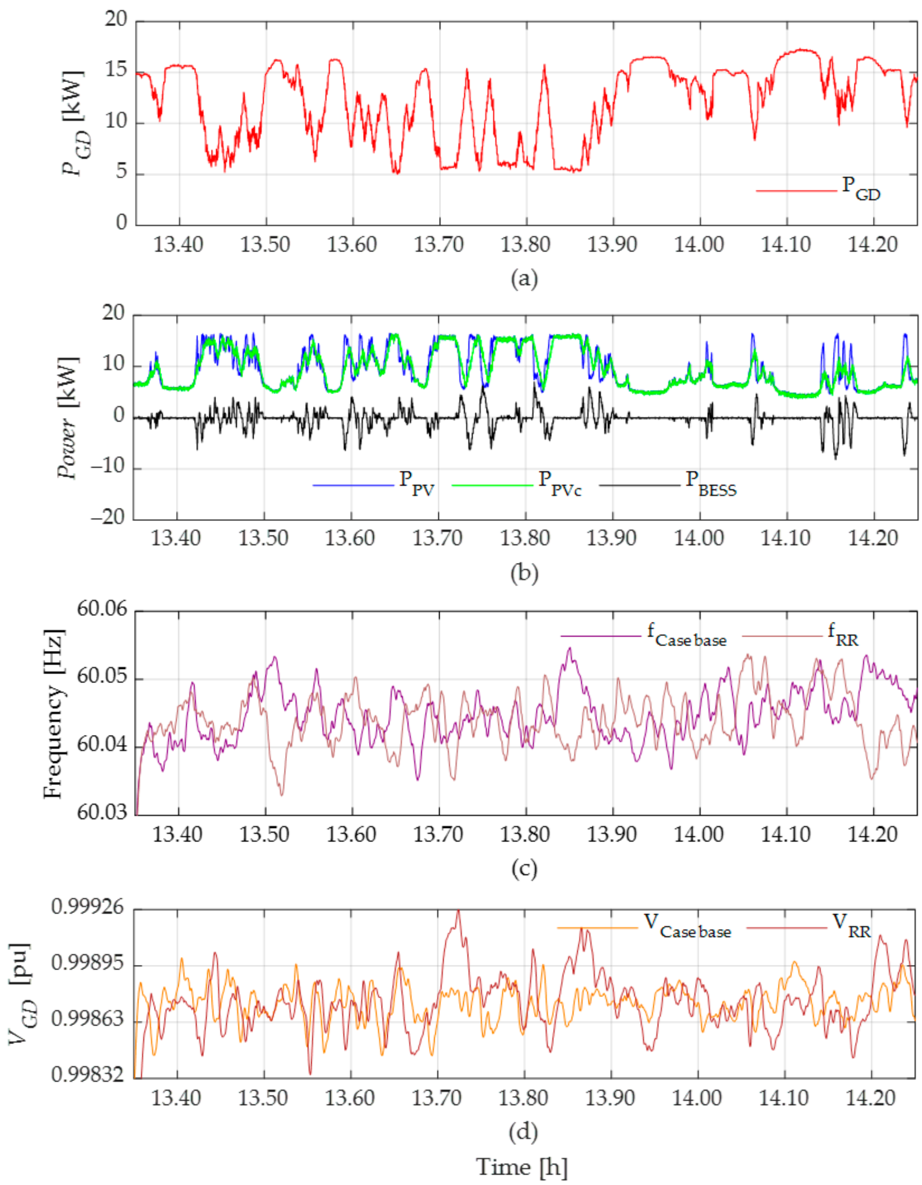

Figure 10. Experimental outcomes of applying the R-R filter method for V2G to smooth PV power: (**a**) GD power, (**b**) PV power compensated with Psc, (**c**) generator frequency, and (**d**) generator line voltages.

The experimental outcomes of the V2GSUN method employing a variable time window size through FLC are summarized in Figure 11. This figure illustrates the emulated power profiles. Figure 11a presents the GD power response, where the impact of the V2GSUN method on power stability is evident. Compared to previous approaches, Figure 11b demonstrates improved effectiveness In power smoothing tasks. Additionally, Figure 11c shows the improved GD frequency response, indicating significantly reduced frequency variability compared to the baseline case. Figure 11d displays the GD voltage response, illustrating minimized fluctuations. These results underscore the capability of the V2GSUN method to enhance both frequency and voltage stability, affirming its suitability for optimizing grid-connected systems.

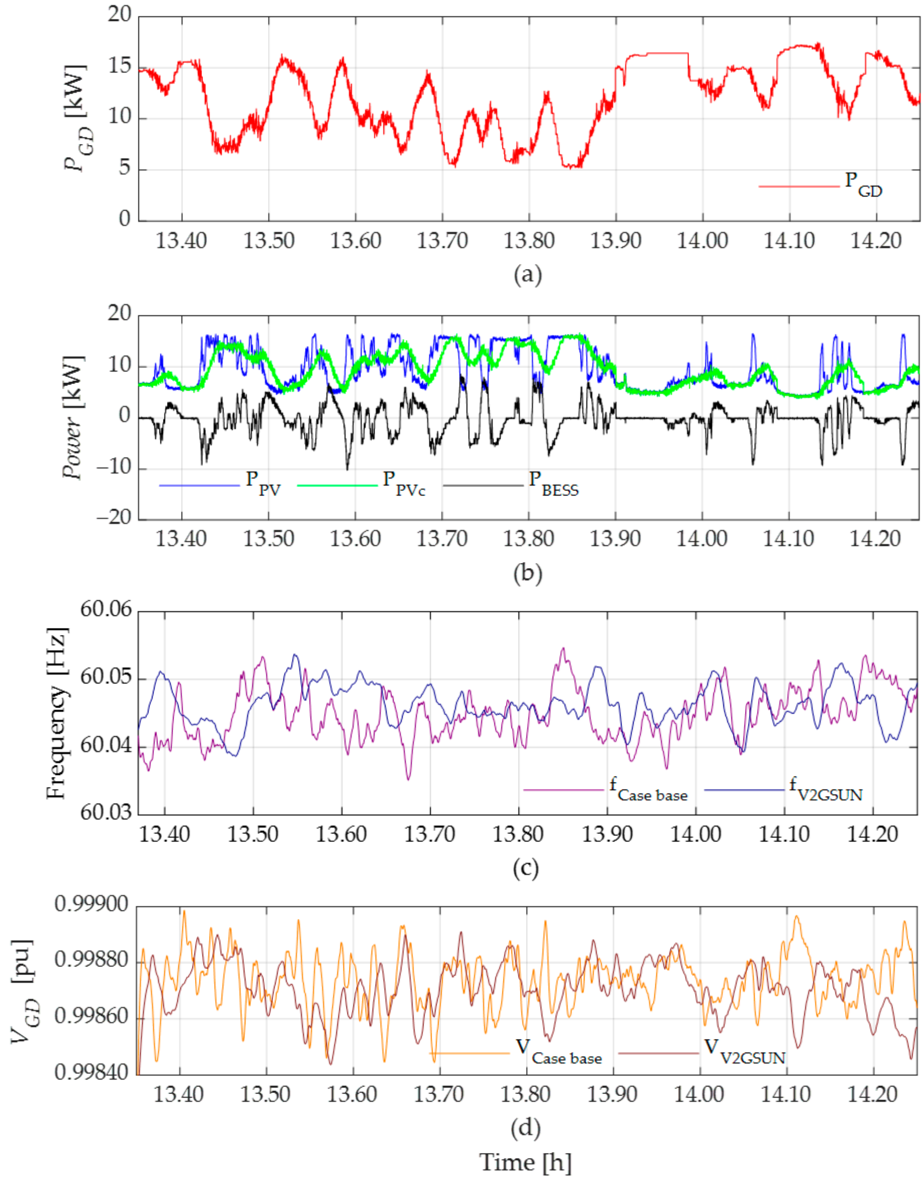

Figure 11. Implementation of the proposed "V2GSUN" algorithm for V2G to mitigate PV intermittence: (**a**) GD power, (**b**) PV power compensated with Psc, (**c**) generator frequency, and (**d**) generator line voltages.

In the comparative analysis conducted so far, the proposed V2GSUN method demonstrates superior performance in stabilizing power fluctuations and maintaining consistent voltage levels compared to the traditional MA and RR methods. Incorporating an FLC to adjust the time window size dynamically allows for more precise power smoothing, resulting in improved grid stability and efficiency. These findings underscore the potential benefits of implementing advanced control strategies in V2G systems to optimize renewable energy integration and enhance overall energy management in isolated MG. Figure 12 depicts the frequency variability after implementing the proposed method and compares it with the other two reference methods and the base case study. Figure 12 shows the frequency response using the MA, R-R, and MA methods enhanced with FLC (V2GSUN). The V2GSUN method demonstrates satisfactory performance by significantly reducing frequency variation, thereby maintaining system operation within safe frequency values and highlighting its effectiveness in this specific case. This underscores the ability of the proposed method to enhance grid stability by effectively managing power fluctuations.

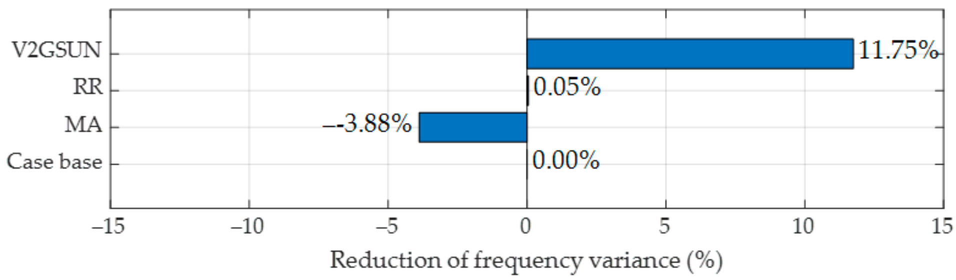

Figure 12. Indicators of frequency variability reduction achieved in each case of study: MA filter using FLC (proposed V2GSUN method), R-R filter, MA filter, and case base.

In this analysis, we began by calculating the variance for each method: the base case variance (Equation (2)), the moving average method variance (Equation (3)), the ramp-rate method variance (Equation (4)), and the V2GSUN method variance (Equation (5)). Then, these variance values were grouped into a variance vector (Equation (6)). Finally, the percentage reduction in variance relative to the base case variance was calculated (Equation (7)).

$$Var_{cb} = Var\left(f_{GD}^{cb}\right) \tag{2}$$

$$Var_{MA} = Var\left(f_{GD}^{MA}\right) \tag{3}$$

$$Var_{RR} = Var\left(f_{GD}^{RR}\right) \tag{4}$$

$$Var_{V2GSUN} = Var\left(f_{GD}^{V2GSUN}\right) \tag{5}$$

$$Variances = [Var_{cb}\ ,\ Var_{MA}\ ,\ Var_{RR}\ ,\ Var_{V2GSUN}] \tag{6}$$

$$Reduction\ percentage = 100 \times \left(1 - \frac{Variances}{Var_{cb}}\right) \tag{7}$$

In studies related to V2G, it is common practice to examine the behavior of the SoC of the batteries to monitor their usage while implementing any control technique. Hence, the behavior of the Li-Ion BESS's state of charge for each power smoothing methodology is summarized in Figure 13. The black line color depicts the SoC state using the MA method, green shows the SoC response with the R-R method, and brown illustrates the SoC response to the MA method integrated with FLC (V2GSUN).

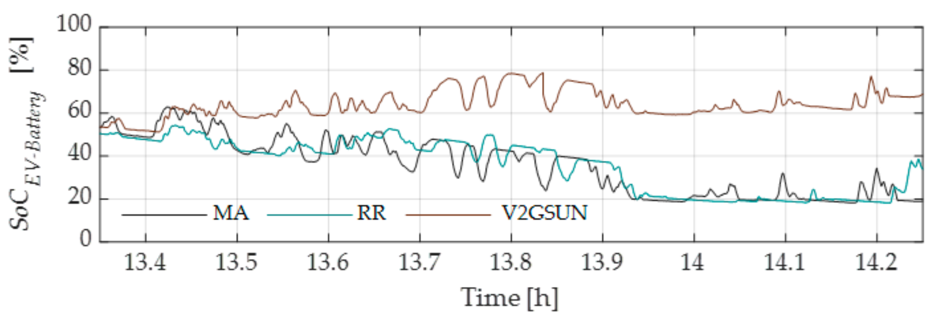

Figure 13. The behavior of Li-Ion BESS's SoC by implementing diferent V2G power smoothing approaches: MA filter, RR filter, and MA filter using FLC (V2GSUN).

The V2GSUN method performs satisfactorily by keeping the storage system operation within safe limits, which is crucial for prolonging the battery lifespan and ensuring efficient energy management.

Figure 14 presents the resulting smoothing factor, indicated by the time window size WS generated by the FLC. An in-depth analysis shows its compliance with the fuzzy rules outlined in Table 1. The graph in Figure 14 offers insights into the alignment between the achieved smoothing factor and the predefined fuzzy rules. This alignment ensures that the dynamic adjustments made by the FLC are consistent with the desired smoothing objectives, leading to optimal power smoothing and enhanced grid stability. The real-time adjustment feature of the V2GSUN algorithm facilitates a responsive and adaptive approach to alleviate PV power fluctuations, further validating its applicability in real-world scenarios.

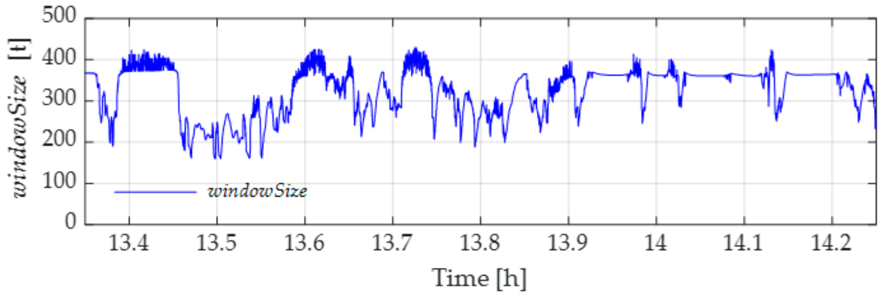

Figure 14. Real-time window size updating is featured in the proposal (V2GSUN).

Table 2 summarizes the results from various methodologies proposed for mitigating variability in renewable energy sources (RES) by considering the initial SoC conditions of the storage system. Each laboratory test started with an initial SoC set at 50%. These techniques successfully smoothed renewable power generation by adjusting the output according to the SoC percentage within the designated range. The findings reveal that using the proposed V2GSUN method decreased variance by 19.43%, from 15.6% without Li-Ion integration to 12.58% with it.

Table 2. Results of energy generation were obtained by applying the power smoothing methodologies studied.

(50%) SoC_{SC} Initial	Variance without Compensation	Variance with Compensation	Variance Reduction (%)	Renewable Energy Delivered without Compensation (kWh)	Renewable Energy Delivered with Compensation (kWh)	Energy Difference (kWh)
MA	15.66	13.07	16.55	3.21	3.17	0.03
RR	15.91	13.65	14.2	3.21	3.15	0.05
V2GSUN	15.62	12.58	19.43	3.23	3.20	0.04

Table 3 shows that the V2GSUN method improves the variance of the grid frequency provided by the GD from the baseline case, reducing it from 1.5617 to 1.3782. This implementation of V2GSUN results in an improvement of 11.75%.

Table 3. Results of frequency variation when applying different power smoothing methodologies in the V2G context.

	Variance of Reduction Frequency (%)
Case base	1.5617
MA	1.6263
RR	1.5610
V2GSUN	1.3782

4.2. Study Scenario 2: Li-Ion Storage System with Low SoC Level

In this second study scenario, the Li-Ion Storage System began operating at 20% of the full capacity, prioritizing EV charging, as can be seen in Figure 15b. The objective is to ensure that the lithium-ion battery is used in an electric vehicle through a Vehicle-to-Grid (V2G) system. Figure 15b demonstrates that using the MA filter with FLC reduces variance by 16.05%. Figure 16 illustrates the Li-Ion battery's SoC beginning to charge and reaching 60%, focused on its recharge over mitigating power fluctuation and effectively utilizing peaks in renewable energy.

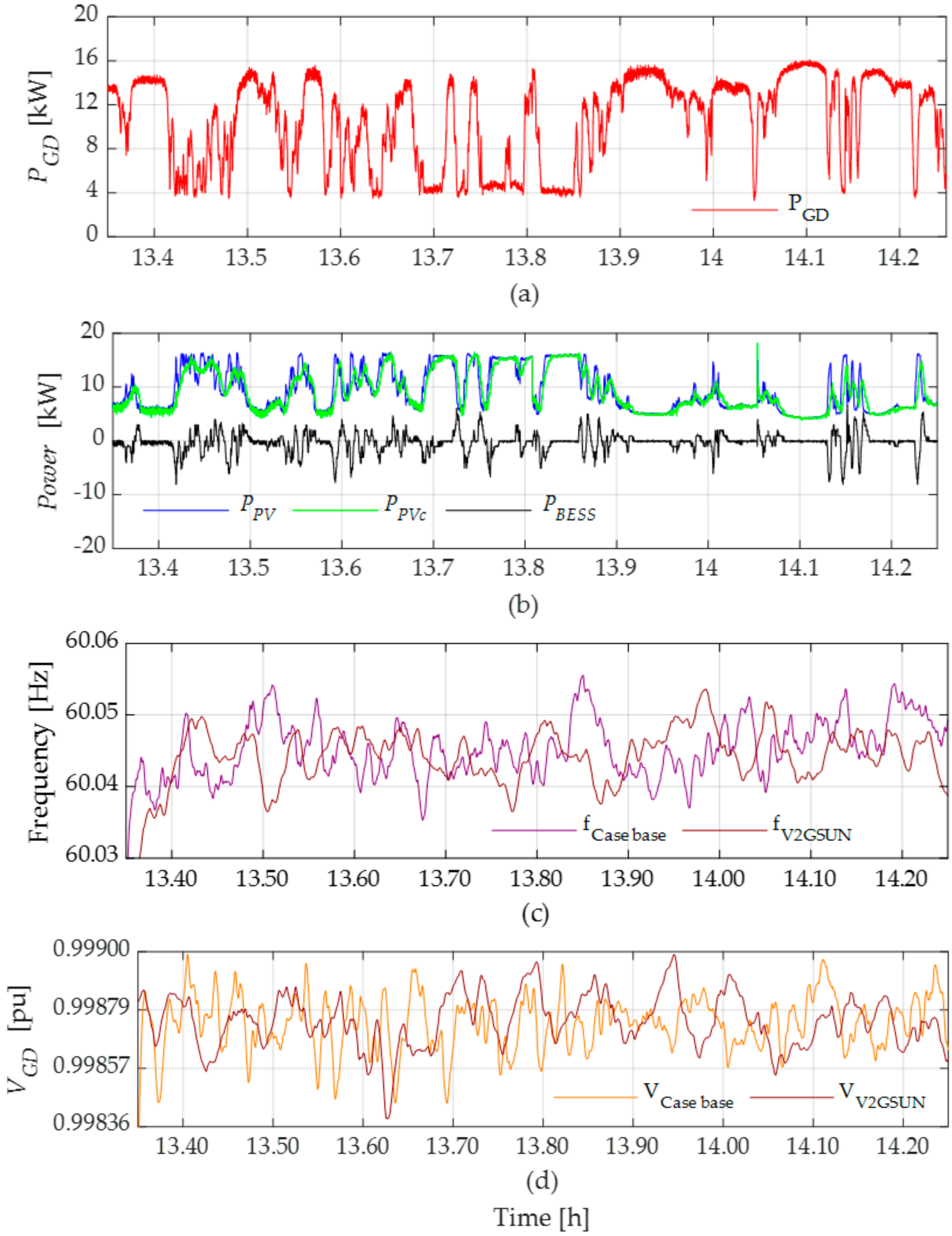

Figure 15. Experimental test outcomes by applying the V2G concept with the proposed "V2GSUN" filter method for charging priority: (**a**) GD power. (**b**) PV power compensated with Psc. (**c**) generator frequency, and (**d**) generator line voltages.

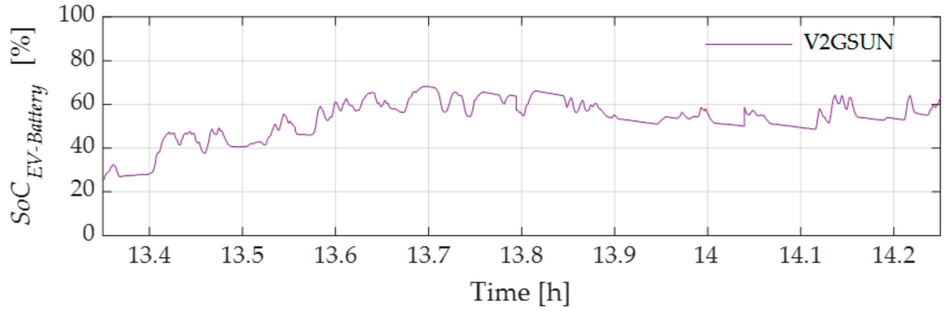

Figure 16. Result of prioritized SoC charging for storage system using V2G while mitigating generated power peaks.

Table 4 shows the results of Study 2, which focuses on smoother energy to reduce the initial percentage of beef to decrease the change in beef production. This method prioritizes charging in electric vehicles, from 20% SoC to 60% SoC. This method makes energy production stable, and the power source adjusts according to the current status of SoC. Outcomes show that the variance with the MA filter method compared to V2GSUN was reduced by 16.05%. Figure 17 establishes the temporal progress with smoother factors in FLC output WS data.

Table 4. Results of renewable energy production with the application of the compared power smoothing methodologies.

(20%) SoC_{SC} Initial	Variance without Compensation	Variance with Compensation	Variance Reduction (%)	Renewable Energy Delivered without Compensation (kWh)	Renewable Energy Delivered with Compensation (kWh)	Energy Difference (kWh)
V2GSUN	15.63	13.12	16.05	3.21	3.06	0.15

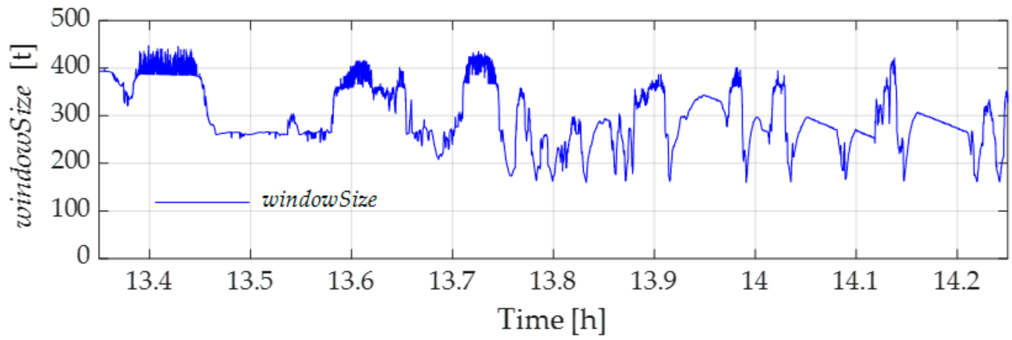

Figure 17. Real-time adjustment of data window size (t).

4.3. Sensibility Analysis for Implementing V2G

Several power smoothing methods are compared in this section in terms of performance against several key metrics: standard deviation, crest factor, form factor, ripple index, and coefficient of variation. The methods evaluated include the baseline case, MA, RR, and two variants of the V2GSUN method with different SoCs of 50% and 20%. Figure 18 provides a compact analysis of the power smoothing metrics achieved by the proposed method. The standard deviation, a measure of data dispersion around the mean, showed significant improvement with the V2GSUN method at 50% SoC, achieving the lowest value (3.540) compared to the baseline (3.950), indicating enhanced consistency and reduced variability in power generation. Although the crest factor, which evaluates the relationship between peak values and the root mean square (RMS) value, showed no notable improvements with the smoothing methods, the baseline case had the lowest value (1.632), indicating fewer extreme peaks. The MA and RR methods showed higher crest factors

(1.651 and 1.652, respectively), suggesting more frequent peaks. The form factor, which measures the uniformity of data distribution, also highlighted the V2GSUN method at 50% SoC, with the lowest value recorded (1.061), suggesting a more consistent signal than the baseline case (1.084). The ripple index, indicating signal variation relative to its mean, was significantly reduced with the V2GSUN method at 50% SoC (0.354), demonstrating smoother and more stable power generation compared to the baseline (0.418). Similarly, the coefficient of variation, assessing variability relative to the mean, was lowest with the V2GSUN method at 50% SoC (0.354), showing the least relative dispersion and greatest consistency in power generation. At the same time, the baseline case had the highest value (0.418), reflecting the most significant relative variability.

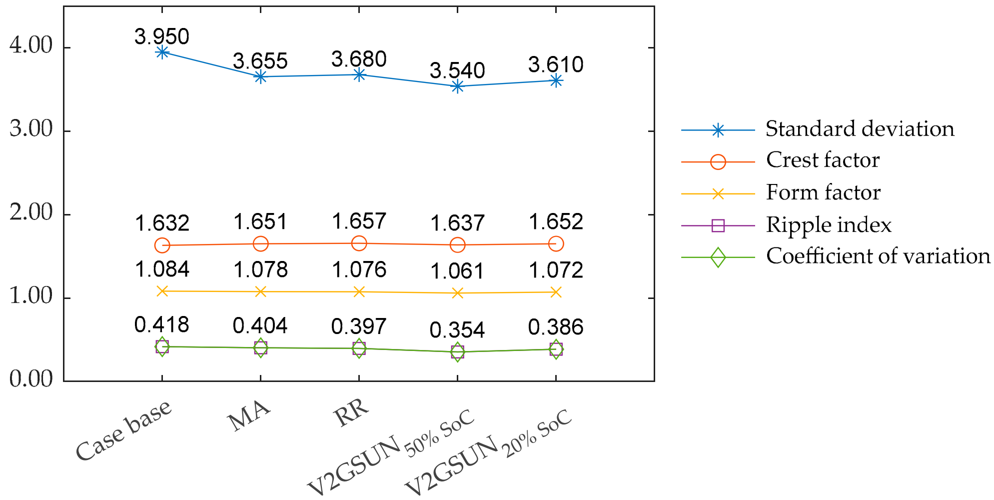

Figure 18. Results of sensibility analysis of power smoothing metrics.

5. Conclusions

This study introduces the innovation method, the V2GSUN soft effect method, aimed at improving the performance of isolated electrical grids. This method is an advanced version of the MA method integrated with FLC. There is definitely great progress once it is approved in the laboratory.

Adapting lithium-ion storage batteries to various SoC levels demonstrated its effectiveness in maintaining a safe operational range. The proposed method significantly reduces power changes, asserting its ability to smooth renewable balancing capacity.

Furthermore, this study demonstrates a multifunctional approach to address specific operational goals as the prioritization of the EV charging process. These findings show a significant reduction in time-domain power changes and emphasize the potential of the advanced V2GSUN method to optimize Ev charging operation. This includes achieving efficient energy stability to ensure appropriate communities in electric vehicle batteries to meet future user needs and improvement of the low-inertia power system operation.

The comparative analysis of two well-known traditional smoothing techniques reveals that the proposed V2GSUN method delivers a more stable smoothing effect while reducing the high variability of the variables of interest. Although the MA and R-R methods excel in One-Treg, the V2GSUN method consistently produces a smoother power curve. Selecting the appropriate method should take into account the specific characteristics of renewable energy systems as well as the unique requirements and priorities of electric vehicles.

Finally, it must evaluate indicators such as standard deviations, final factors, shape factors, wave index, and mutant coefficients, supporting the more significant effect of superiority recommended for the net environment (V2G). Compared to the alternative method, the V2GSUN method shows significantly reduced variation in consistency, improves stability, and consistent energy production. This emphasizes its potential to enhance grid stability and optimize renewable energy and electric vehicle technology integration.

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