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Innovative Power Smoothing Technique for Enhancing Renewable Integration in Insular Power Systems Using Electric Vehicle Charging Stations

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Abstract: The reliance on imported fuels for electricity generation and internal transportation in insular electrical systems has historically posed a significant challenge due to their geographic isolation. The vulnerability of insular ecosystems to pollution has driven the need to transition toward renewable energy sources. Despite their inherent variability, wind and solar energy have gained acceptance. Integrating these renewable technologies into insular grids presents technical challenges that impact the quality of the power supply, particularly with the increasing presence of electric vehicles. Nevertheless, the batteries of these vehicles provide an opportunity to enhance network performance. This article introduces an innovative power smoothing technique that utilizes electric vehicle batteries to optimize self-consumption and reduce power fluctuations. The proposed method is an enhanced version of the ramp-rate energy smoothing method, incorporating adaptability through real-time control of the ramp-rate using fuzzy logic. It employs an aggregated model of lithium-ion batteries with a bidirectional power electronic converter. Experimental validation is carried out in the Micro-Grid Laboratory of the University of Cuenca, Ecuador. Experimental results demonstrate a significant 14% reduction in energy generation variability, resulting in a more stable electrical supply profile. Additionally, there is a marginal improvement in energy delivery, with an additional injection of 0.23 kWh compared to scenarios without the participation of electric vehicle batteries in power smoothing tasks. These findings support the effectiveness of the proposed approach in optimizing the integration of intermittent renewable generators and electric vehicle charging in insular energy systems.

Keywords: insular electrical systems; renewable energy integration; electric vehicle batteries; power smoothing; V2G

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1. Introduction

In an environment marked by the growing demand for sustainable energy sources and the consequent reduction in dependence on conventional resources, island power systems stand at the forefront of innovation. Their geographical isolation imposes the need to import fossil fuels for electricity generation and internal transportation, thereby driving the exploration of autonomous and environmentally friendly energy solutions [1,2]. The progressive integration of renewable sources, such as photovoltaic (PV) and wind power (WP) systems, has represented a transformative step towards energy self-sufficiency [3,4].

However, the intermittent nature of these sources and their remote locations pose substantial challenges to maintaining stability in island power grids [5]. The widespread adoption of electric vehicles (EVs) emerges as a viable strategy to mitigate WP and PV energy fluctuations [5–7]. This viability hinges on the ability to program electric vehicle charging stations (EVCS) to charge or discharge an EV battery energy storage system (BESS) according to energy demand [6]. Efficiently coordinating the charging and discharging schedule of EVs, aiming to increase self-consumption and reduce power fluctuations, presents a significant challenge, especially due to the low adaptability of the ramp-rate (R-R) to respond to sudden changes in renewable energy production. In this context, the energy loss resulting from the necessary load adaptation to new production can disrupt key parameters of the power grid. This study focuses on this issue, proposing an innovative method to reduce WP and PV fluctuations using the EV BESS in an off-grid system based on fuzzy logic and the R-R technique.

Frequency and voltage stability in a power system are critical for optimal operation, especially in isolated systems with limited robustness. For this reason, some electric distribution companies impose limits on the ramp-rate of PV or WP, as described in [7,8], setting a maximum R-R of 10%/min to prevent destabilization of the power grid. This challenge is exacerbated when a fleet of EVs connects to the grid randomly without proper coordination between generation and demand. EV charging can occur in locations such as parking lots, corporate facilities, public areas, or at home, according to [6]. This study explores two grid connection approaches: vehicle-to-grid (V2G) and grid-to-vehicle (G2V). EVs can be charged during off-peak hours and inject surplus energy back into the grid through their bidirectional power converters.

There is extensive literature on power smoothing methods applied to renewable sources. For example, the authors in [9] introduce an innovative approach to mitigate wind power fluctuations by dynamically adjusting the time constant of a purposefully crafted adaptive first-order low-pass filter controlled by a fuzzy logic system. This optimization is achieved by integrating a supercapacitor-based energy storage system. The authors in [10] develop a delta control to limit the R-R of a wind farm, highlighting that these limitations can reduce its total energy performance by 18%. Despite the efforts of some wind or PV farms opting for the installation of energy storage systems (ESS) to avoid the reduction in energy productivity, as described in [11], ESS installation is perceived as expensive and environmentally unfriendly. Therefore, leveraging the EV BESS as a demand response mechanism becomes vital for smoothing energy instead of installing battery banks.

Power fluctuations from renewable sources can cause premature aging of the BESS by subjecting it to intense charge/discharge cycles, as discussed in [12]. The authors in [13] employ a fuzzy logic algorithm for ESS energy allocation, where the fuzzy controller determines the filter cutoff frequency based on the state of charge (SoC) of the ESS. An analytical model seeking to calculate the available power capacity in a V2G parking lot is presented in [14]. However, the central challenge in this context lies in the uncertainty associated with the amount of power and energy each electric vehicle can supply. Ref. [15] describes a fuzzy controller that sets the battery power, considering SoC and mismatch power. In this context, the unit with the highest SoC injects more energy and absorbs less. Some studies, such as [16,17], focus on determining the optimal size of the BESS used in EVs. In [18], a learning action automaton is implemented and validated, including two WPs, two battery exchange stations for EVs, and distributed EV penetration. The simulation results indicate interaction between EVs in a mixed-modal environment.

The most commonly employed conventional strategies are based on applying filtering techniques using ESS to establish the reference power intended for compensation. Information on design approaches for fluctuation attenuation using ESS in combination with various types of filters, including the first-order low-pass filter, the second-order low-pass filter, and especially R-R filters, has been widely disseminated [19–21].

The ramp-rate (R-R) technique limits the speed at which power can increase or decrease. Although it is an easy, simple, yet effective solution for smoothing, choosing the appropriate ramp-rate remains a significant research problem. Most studies focus on reducing power fluctuations from renewable sources or optimizing energy using EVs as storage, but few studies simultaneously analyze both strategies, especially in isolated systems. A promising solution is to adjust the ramp-rate in real-time based on the changing conditions of renewable sources and EVs, as demonstrated in [22], where they adjust the time constant of a low-pass filter in real-time to reduce computational load due to ramp-rate adjustment of various sources and intermittent loads. Additionally, researchers in [13] demonstrate that using fuzzy logic algorithms improves the designation of reference powers for a BESS. In [23], two high-frequency attenuation filters calculate the powers associated with a BESS, and a fuzzy controller sets the filter cutoff frequency based on SoC.

Notably, these approaches do not consider the direction of energy variations or application in EVs. Primarily, these methodologies are centered around validating the efficacy of smoothing techniques and involve meticulously utilizing the available ESS energy. However, when dealing with an electric vehicle, it becomes crucial to ensure that, following the provision of power smoothing services, the battery remains fully charged when the user unplugs their vehicle from the EV charging station. After a thorough review, some gaps in the literature have been identified that need to be addressed, which are described below:

- While ref. [24] presents a coordinated strategy of ESS and power smoothing, exploring and optimizing the use of stored energy in EVs is necessary, considering multiple renewable sources.
- Investigate the specific impact of uncoordinated interconnection of electric vehicle (EV) fleets on island power systems, considering the variability in EV charging and discharging and its influence on network stability, complementing the study presented in [11].
- Analyze how to dynamically adjust the ramp-rate in real-time according to the changing conditions of renewable sources and EVs based on fuzzy logic to improve system efficiency and stability, inspired by [13,22].
- Explore how considering the direction of energy variations can influence the management of RES-EV hybrid systems for more precise planning.
- Careful consideration is needed to compromise the demands of power smoothing while maintaining EV batteries at adequate state of charge levels for users' future needs.
- Investigate the optimal coordination between V2G-power smoothing modes to maximize efficiency and minimize impact on the grid.

To address these gaps, this study presents an innovative power smoothing method called V2GSmooth based on the ramp-rate technique to control the charging and discharging speed of electric vehicle (EV) batteries, avoiding unnecessary energy loss during load adaptation to new production. This is achieved by adjusting the maximum R-R of the lithium-ion (Li-Ion) BESS in real-time according to the actual conditions of renewable sources and EVs using fuzzy logic. This proposal carefully comprises the effectiveness of power smoothing while ensuring the EV batteries remain at optimal charging levels for users' subsequent use, striking a balance between grid stability and user convenience. The method is experimentally validated on a laboratory test platform. The rest of the article is organized as follows: Section 2 presents the materials and methods, explaining the proposed method; Section 3 shows the case study; Section 4 presents the results and discussion of the experiments; and Section 5 concludes the article.

2. Materials and Methods

Figure 1 schematically illustrates the methodology applied in this study. In the initial phase, input data are gathered, comprising the actual output power from PV and WP, measured in the laboratory during a typical day.

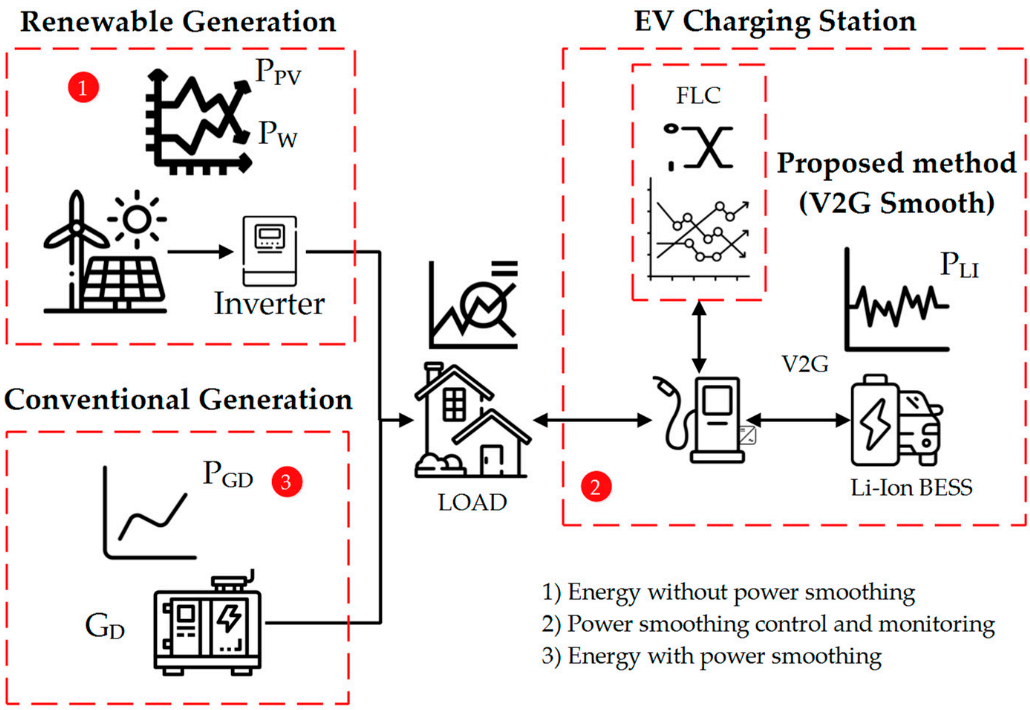

Figure 1. Representative schematic of the proposed methodology.

The proposed method is introduced in the subsequent phase, defining the rules for fuzzy logic control (FLC). This control aims to adjust the maximum R-R of the Li-Ion BESS for real-time power smoothing. To achieve this, the supervisory control of the Li-Ion BESS system is examined through the data logger of the experimental microgrid.

The method is compared with conventional moving average (MA) or traditional ramp-rate (R-R) methods. Notably, a Li-Ion BESS is utilized to emulate the BESS of an EV, specifically an electric van (Model: BYD T3) available in the laboratory. This EV is characterized by a notable energy storage density and the capability to achieve the desired performance. The EV BESS is connected to the grid through a bidirectional three-phase inverter (50 kW), through which the proposed method is implemented in the embedded computer control system.

Finally, the obtained results are experimentally validated under various technical criteria, accompanied by a comprehensive analysis of variability and energy.

2.1. Development of a Power Smoothing Algorithm Based on the R-R Method

The primary objective of applying the R-R method in energy generation systems, such as PV or WP, is to mitigate abrupt fluctuations and enhance stability in energy production through a controlled and gradual power change [25]. The central premise of the R-R method involves establishing upper and lower limits for the permissible power change rate [26]. This ensures that any variation in power occurs gradually within that defined range.

The power change rate at time instant i is calculated as the difference between the current total output power ($P_T(i) = P_{PV}(i) + P_W(i)$) and the previous smoothed power value $P_T(i-1)$, which has already undergone smoothing. This is expressed in Equation (1) [27].

$$rr(i) = \left|\frac{dP_T}{dt}(i)\right| = \left|\frac{P_T(i) - P_T(i-1)}{t(i) - t(i-1)}\right| \tag{1}$$

The control algorithm operates at equal time intervals of Δt seconds. In our study, $\Delta t = t(i) - t(i-1) = 0.1$ s. Equation (2) calculates the power rate of change (*roc*) by subtracting the previously smoothed power from the current power value. This variation activates or deactivates the algorithm's condition if it falls within the assigned variable limit, adjusting accordingly.

$$roc(i) = P_T(i) - P_T(i-1) \quad (2)$$

2.2. Proposed Control Strategy

The proposed control strategy is implemented in a Li-Ion BESS, which is connected to the grid via a bidirectional power inverter. This inverter enables precise control of active and reactive power injection and absorption. Controlled conditions were defined in this study to assess the effectiveness of our proposal. The standalone diesel generator is connected to an off-grid bus bar and acts as a three-phase voltage source, thus providing the voltage and frequency reference to the isolated grid. This isolated bus bar seamlessly integrates the inverters associated with the wind and photovoltaic power systems (PV and WP, respectively) and the emulated EV BESS. Our main goal was to smooth PV and WP power fluctuations, achieving a more uniform power injection into the grid facilitated by the energy cushion of the Li-Ion BESS.

To achieve this objective, we implemented an innovative strategy that enhances the effectiveness of the R-R method through the use of FLC. This FLC function serves as a control system that dynamically adjusts the power change rate limits based on the input energy (PV and WP) and the state of charge (SoC) of the Li-Ion BESS. The output of the FLC provides an adjustable power change rate over time, allowing flexibility when the load is high and resources are limited. Figure 2 presents the overall block diagram of the proposed controller. The algorithm takes as input the measurement of injected active power (PV and WP) and the SoC of the Li-Ion BESS. The proposed method utilizes predefined fuzzy rules to make decisions that directly influence the dynamic ramp-rate (%R-R), adapting it to the real-time power smoothing requirements. Thus, the output variable is conditioned by the actual state of the input variables P_T and the SoC of the storage system.

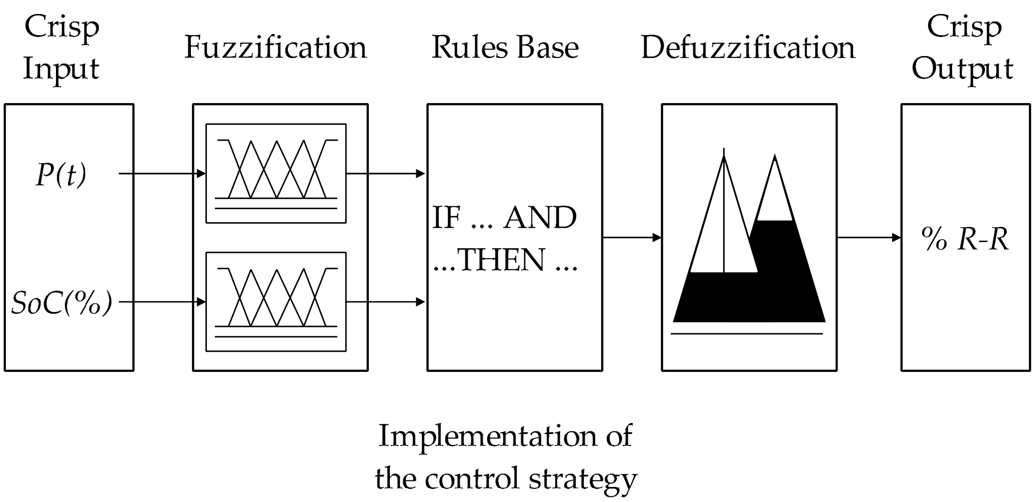

Figure 2. Schematic representation of the fuzzy logic controller (FLC).

The R-R percentage is adjusted by applying fuzzy logic using the smoothing factor to optimize the state of charge of the Li-Ion BESS in real-time. Thus far, the literature has not described its value by relating it to the active power of PV or WP and the SoC of the Li-Ion BESS in real-time. This work introduces a heuristic method for its determination.

Table 1 details the control rules for the proposed strategy in this article, where NS = No Smoothing, LS = Low Smoothing, S = Smoothing, MS = Moderate Smoothing, HS = High Smoothing, VL = Very Low, L = Low, M = Medium, H = High, and VH = Very High. In addition, Figure 3 displays the membership functions of the FLC. The controller adapts the ramp-rate percentage at each moment based on the variations in power and the SoC of the Li-Ion BESS. Triangular and trapezoidal group membership functions are employed in the design of fuzzy values. Finally, the centroid method is used for defuzzification. Figure 4 presents the resulting surface showing the variation of the two inputs and the output when evaluating the FLC.

Table 1. FLC Rules.

		P [kW]				
		VL	L	M	H	VH
SoC [%]	VL	NS	S	MS	HS	VHS
	L	S	NS	S	MS	HS
	M	MS	S	S	S	MS
	H	HS	MS	S	HS	MS
	VH	VHS	HS	MS	VHS	VHS

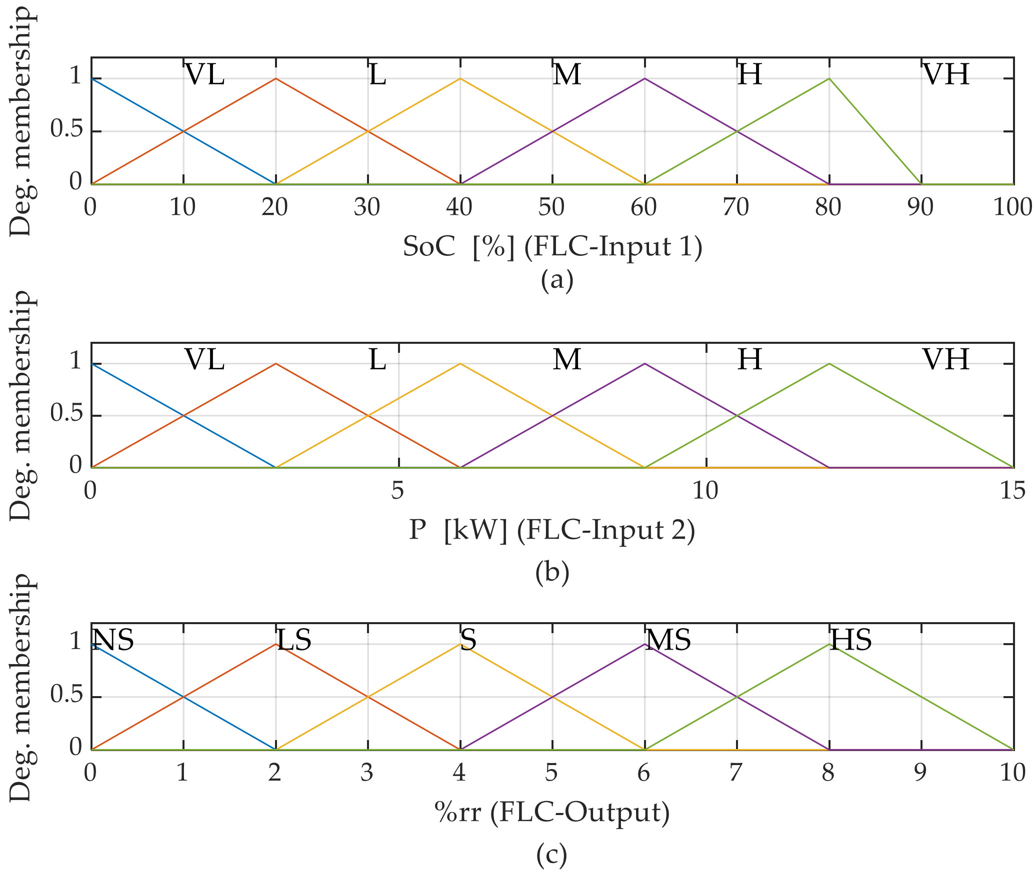

Figure 3. Membership Functions of the Proposed FLC: (**a**) Input 1: P, (**b**) Input 2: SoC, and (**c**) Output: Smoothing Factor (%R-R). NS = No Smoothing, LS = Low Smoothing, S = Smoothing, MS = Moderate Smoothing, HS = High Smoothing. Input 1 Values: VL = Very Low, L = Low, M = Medium, H = High, VH = Very High. Input 2 Values: Very Low = 10%, Low = 30%, Medium = 50%, High = 70%, Very High = 90%.

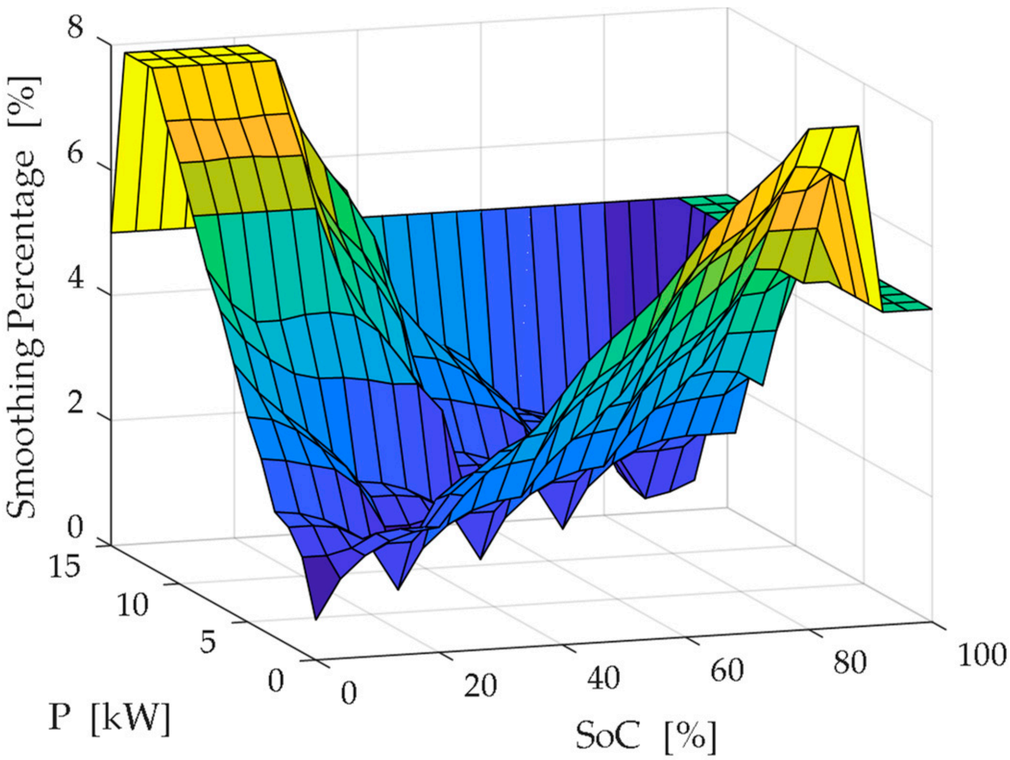

Figure 4. Input and output of the designed FLC.

2.3. Used Life Cycles of the Lithium Battery

As the Battery Electric Vehicle (BEV) engages in the fluid dynamics of charging and discharging cycles, it encounters challenges that may influence its overall usage and wear characteristics. Unraveling these intricacies becomes imperative for crafting sustainable and effective V2G methodologies. According to [27], battery aging can be categorized into two major facets: calendar aging and cyclic aging. Calendar aging is primarily associated with battery storage, representing periods with no charging or discharging, commonly known as passive aging. On the other hand, cyclic aging corresponds to the impact of battery usage on the State of Health (SOH), resulting from charging and discharging cycles. In addition, the Equivalent Full Cycle (EFC) concept is a quantitative measure to encapsulate the cumulative impact of charging and discharging cycles on the battery's SOH. The EFC proves to be a valuable indicator, offering a comprehensive overview of battery usage and providing insight into the overall wear and tear experienced by the battery throughout its operational life. However, SOH and EFC indicators are inherently designed for long-term studies.

In this study, we adopt the "Utilized Life Cycles" indicator, leveraging the measured state of charge of the BEV over time. The calculation method, illustrated in Figure 5, involves monitoring the BEV's SoC between two successive samples, Ts, from a recorded dataset with length T_W. This process helps identify whether the SoC is increasing (charging) or decreasing (discharging). Subsequently, these partial segments of SoC are accumulated in two separate auxiliary variables. In a final step, the equivalent number of charging and discharging cycles is determined, allowing for the assessment of the Utilized Life Cycles required to evaluate the BEV's usage during the implementation of the proposed solution in this study within the considered time window.

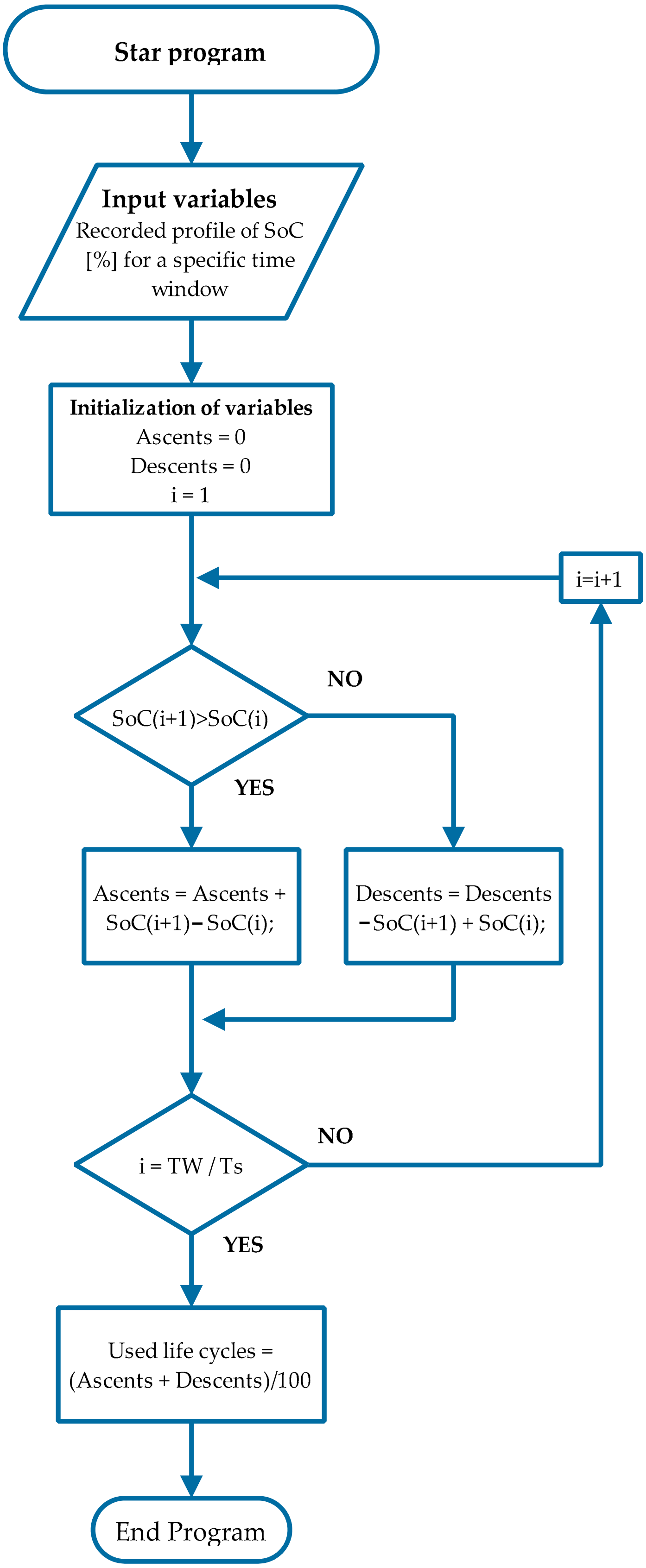

Figure 5. Utilized Life Cycles calculation.

3. Case Study

In this study, algorithms developed in MATLAB were implemented to conduct real-time tests on an isolated microgrid. The microgrid consists of polycrystalline solar panels with an installed capacity of 10 kWp (PV), a single 5 kW variable-speed wind turbine, and the Li-Ion BESS with a capacity of 44 kWh. For this specific case study, the Micro-Grid Laboratory at the University of Cuenca (CCTI-B), Ecuador [28], was utilized. The equipment was configured to establish an isolated network, as depicted in Figure 6, which shows the presence of the solar panel array (P_{PV}), a wind generator (P_W), a thermal diesel generator (GD), a three-phase programmable load $(Load)$, and an EVCS with a BYD electric vehicle, all interconnected with their respective inverters to a network operating at a voltage of 220 V_{AC}. In order to ensure the system's overall power balance, a constant value of 20 kW was set in the three-phase programmable load. The rationale behind maintaining a constant value over time was to create controlled laboratory conditions where power disturbances were solely attributed to intermittent renewable power (solar and wind) injection. This decision was made to eliminate the risk of the thermal diesel generator receiving a reverse power flow when there is an excess of renewable generation, ensuring safe and reliable implementation of the V2G concept. These controlled conditions not only enhanced the system's safety but also contributed to a more accurate and reliable assessment of the effectiveness of the proposed V2G method, as the single power disturbance source was carefully controlled.

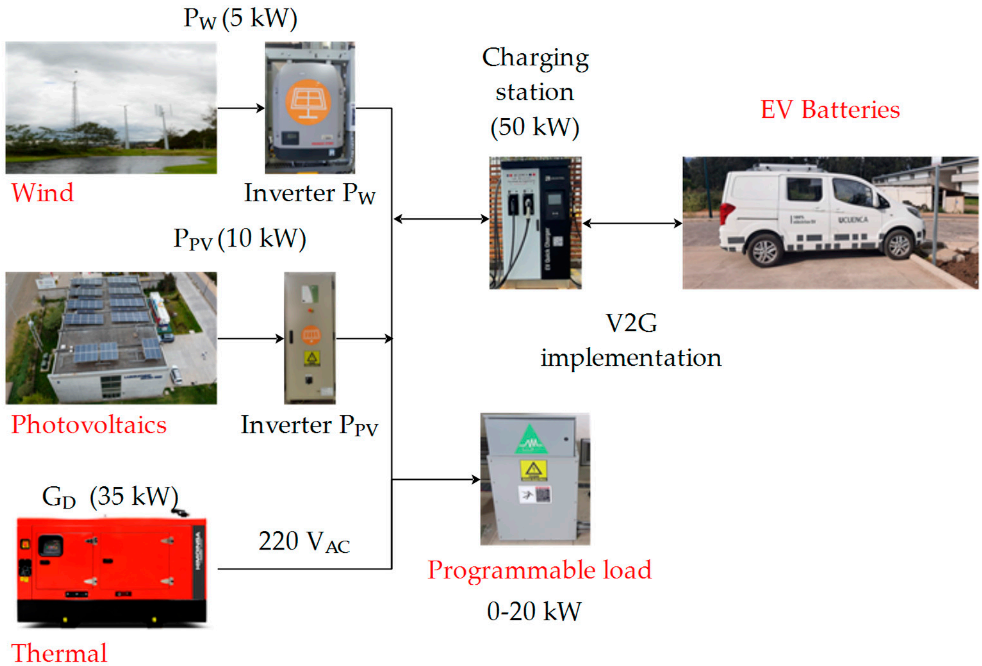

Figure 6. Isolated microgrid of the University of Cuenca laboratory (CCTI-B).

Additionally, the Micro-Grid Laboratory has a BYD van, model T3, with a power of 300 kW and electric motor of 100 kW, called BYD-1814TZ-XS-B35KW. The van's battery belongs to the LiNIMnCo (Lithium, Nickel, Magnesium, and Cobalt) type, with a capacity of 50.3 kWh and total voltage of 438 Vdc. This BESS comprises 12 modules housing 120 cells and has a CCS2-type connector [29].

To emulate the V2G connection, the rechargeable lithium-ion battery bank from the Micro-Grid Laboratory [28] was used. This bank consists of 11 cells of 58.36 VDC, connected in series (model ELPT392-0002, Samsung). The bank's output voltage is 642 VDC, with a power of 88 kW and energy storage capacity of 44 kWh. The BESS bank is connected to a 50 kW power converter that emulates a bidirectional charger, injecting energy from the BESS back into the grid. It also has various adjustable features, such as peak demand management, power stabilization, and energy conversion. This bidirectional power flow enables two modes of electric vehicle operation: G2V and V2G.

It is essential to consider that the variability in daily PV and WP generation can significantly impact the operation and performance of isolated systems and the design and sizing requirements of the Li-Ion BESS or management systems. The analysis and understanding of the daily solar and wind production curve, with both high and low fluctuations, are fundamental for the planning, operation, and optimizing of PV and WP energy equipment, adapting to the specific conditions and needs of each project or application.

In this case, two power curves were considered: one for photovoltaic solar energy (P_{PV}) (see Figure 7, profile highlighted in red) and another for wind energy (P_W) (see Figure 8), randomly selected annually for emulation. The variation in the total power curve delivered to the system ($P_T = P_{PV} + P_W$) can be significant from one day to another, depending on the weather conditions, geographical location, and system characteristics. Figures 7 and 8 represent possible daily power curves with variability based on actual records measured on the roof of the Micro-Grid Laboratory building in the city of Cuenca, Ecuador (WGS84 coordinate system −2.891918819933002, −79.03857439068271) [28].

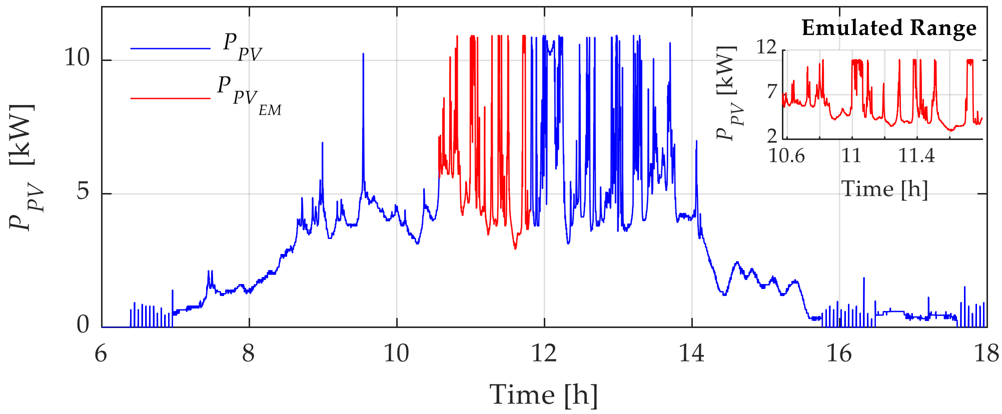

Figure 7. High variability in daily PV power curve.

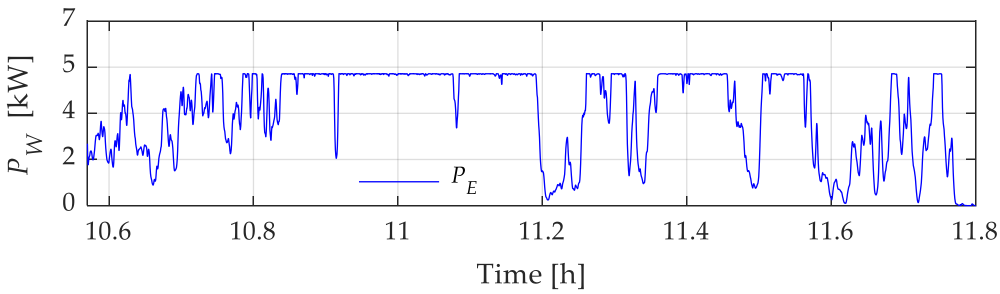

Figure 8. Wind power curve.

For the laboratory test and validation of the effectiveness of the proposed method, approximately 1.2 h of the total power curve (P_T) was emulated (see Figure 9). The choice of this specific segment of the curve for emulation was based on its highly variable behavior, allowing for a more accurate assessment of the proposed method. The goal was to test the method in real-time to obtain a more comprehensive evaluation of the V2G system behavior with the Li-Ion BESS. Notably, the Li-Ion BESS available in the laboratory was used to emulate the power supplied by the PV and WP systems.

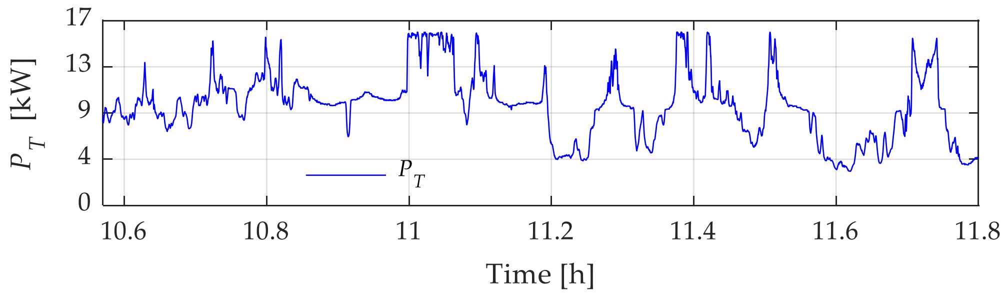

Figure 9. Total power delivered to the isolated system by renewable energy sources.

4. Results and Discussion

This study evaluated the utilization and effectiveness of an enhanced power smoothing method, specifically the R-R filter, by varying its ramp-rate percentage (%R-R) through a fuzzy logic controller (FLC). A comparison was conducted with two previously tested methods in [25], R-R and MA filters, aiming to validate and highlight the proposed improvements. The study was divided into two distinct case studies.

In the first case, comparisons between existing methods and the proposed enhancement were made under conditions based on the SoC percentage of the Li-Ion BESS. In the second case, the new method was implemented with a configuration prioritizing the charging of the vehicle's Li-Ion BESS.

- Case 1: Li-Ion BESS at Medium SoC: In this scenario, it was required that the Li-Ion BESS's SoC be maintained within the range of 20% to 80% as an initial condition.
- Case 2: Li-Ion BESS at Minimum SoC: In this specific undercharge condition, the Li-Ion BESS started its operation with a value below 20% of its maximum storage capacity, prioritizing the vehicle's charging.

These case studies were designed to comprehensively evaluate the proposed enhancement under various operational conditions, allowing for a deeper understanding of its performance and effectiveness in practical situations involving V2G applications.

4.1. Case 1: Comparison and Validation of the Proposal against Conventional R-R and MA Filters

The experimental results are summarized in Figure 10, illustrating the emulated profiles of generated power (blue line), the Li-Ion BESS power (purple line), and the smoothed power output to the grid (red line). In Figure 10a, the smoothing response using the MA method is observed; in Figure 10b, the smoothing response using the R-R method with a fixed ramp-rate is depicted; and in Figure 10c, the smoothing response using the proposed R-R method with a variable ramp-rate through FLC is shown. Figure 11 provides an overview of the Li-Ion BESS's SoC behavior for each power smoothing methodology in this study. Figure 11 represents the SoC status with MA, R-R, V2GSmooth, demonstrating satisfactory performance as the system maintained its operation within safe values (20–80%). This highlighted the effectiveness of the proposed method in this particular case.

Figure 12 depicts the resulting smoothing factor, expressed as a variable percentage of the ramp-rate (%R-R), at the output of the FLC. A detailed analysis revealed proper alignment with the fuzzy rules established in Table 1 and illustrated in Figure 4. The graph in Figure 12 provides insight into how well the obtained smoothing factor adhered to the predefined fuzzy rules.

Table 2 presents the results of various proposed methodologies for power smoothing, aiming to mitigate the variability of RES by applying a condition based on the initial SoC of the Li-Ion BESS. Each test began with a preset initial SoC at 50%. The generated energy was smoothed by implementing these methodologies, providing more or less energy depending on the SoC percentage within the specified range.

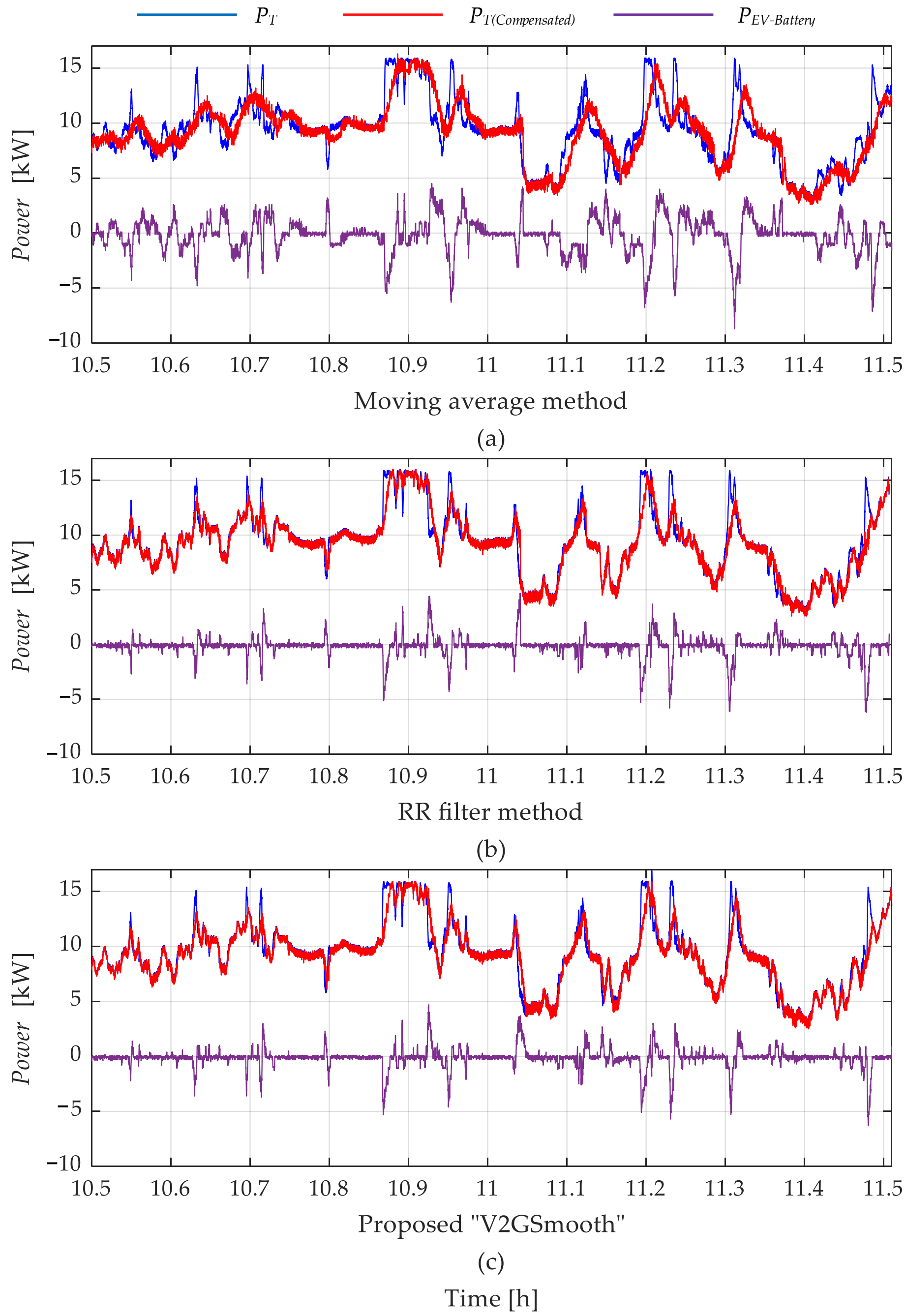

Figure 10. Power response results using V2G with Li-Ion BESS to PV and WP power fluctuations, employing: (**a**) MA filter, (**b**) R-R filter, and (**c**) R-R filter using FLC (proposed V2GSmooth method).

The results indicated that the enhanced R-R filter method through FLC achieved a variance reduction of 12.99%. The variance without Li-Ion was 8.84, while it decreased to 7.43 with Li-Ion. Furthermore, the method resulted in a marginal improvement in energy delivery, with an additional 0.13 kWh of energy injection compared to the case without Li-Ion. In exploring the V2G power smoothing strategies, we meticulously assessed three key methodologies. The MA method emerged as a standout performer, boasting a remarkably high Utilized Life Cycles of 2.803. This emphasized its commendable efficiency in adeptly mitigating temporal variations. Conversely, the R-R method demonstrated resilience to shifts in energy demand, showcasing a slightly lower helpful Utilized Life Cycles of 1.459, indicative of diminished battery wear.

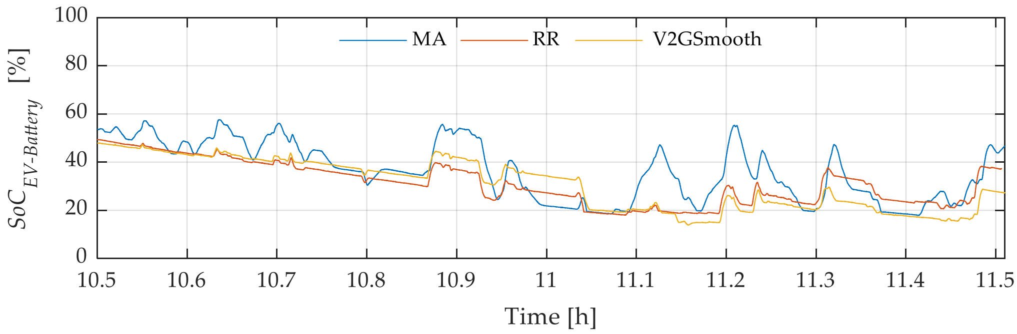

Figure 11. Li-Ion BESS's SoC response results via V2G to PV and WP power variations, employing: MA filter, R-R filter, and R-R filter using FLC (V2GSmooth), respectively.

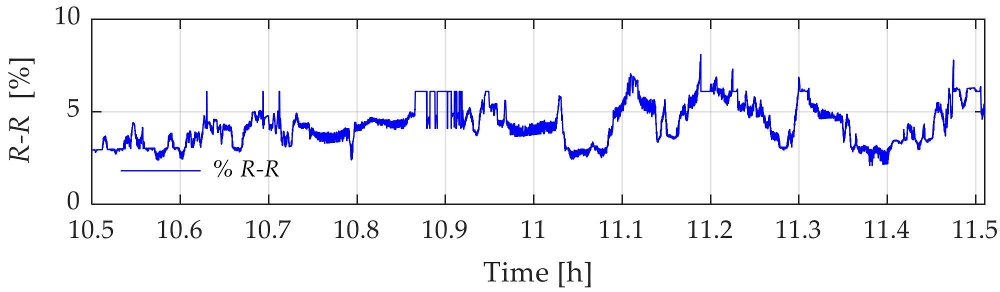

Figure 12. Real-time adjustment of the smoothing factor (%R-R) achieved by the proposed method.

Table 2. Power generation results from 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)	Utilized Life Cycles
MA	8.54	7.61	10.87	9.49	9.3	0.19	2.803
R-R	8.54	7.57	11.31	9.4	9.24	0.16	1.459
V2GSmooth	8.54	7.43	12.99	9.43	9.3	0.13	1.369

The introduction of V2GSmooth, a modified version of R-R incorporating fuzzy logic, achieved a refined equilibrium, attaining a reduced Utilized Life Cycles of 1.369. These findings underscored the importance of choosing smoothing strategies that minimize the number of Utilized Life Cycles. This approach ensures enhanced durability and sustainable battery performance, highlighting a pivotal consideration in selecting effective V2G strategies.

4.2. Case 2: Validation of the Proposal, Prioritizing Li-Ion Battery Charging

A charging condition was implemented for the Li-Ion BESS to harness all peaks of RES power generated for its charging. In this case, an SoC of 20% was set, and over time, it was observed how the Li-Ion BESS prioritized its charging. The goal was to ensure that the Li-Ion BESS was charged for use in the EV through the V2G system. In Figure 13a, the power smoothing through the R-R filter with FLC can be appreciated, achieving a 10% reduction in variance. In Figure 13b, it is observed how the SoC of the Li-ion battery started charging until it reaches 48%, prioritizing its charging over power smoothing and thus taking advantage of renewable energy peaks.

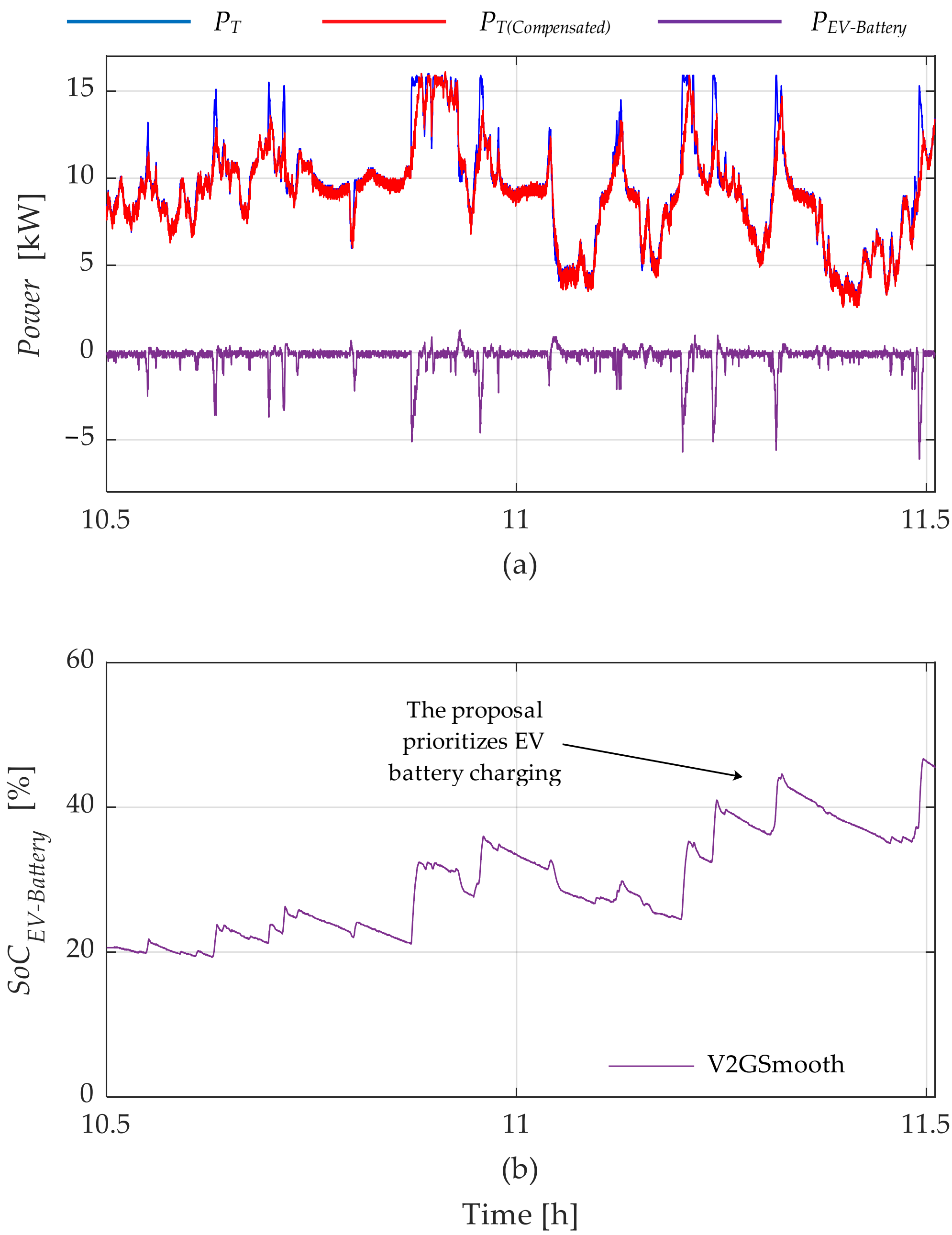

Figure 13. Outcome of SoC prioritized charging for the Li-Ion BESS using V2G, simultaneously mitigating peaks in power generated by RES. (**a**) Power smoothing through the R-R filter with FLC. (**b**) SoC of the Li-ion battery.

Table 3 presents the results of case 2, designed for power smoothing, intending to mitigate variability in RES generation by applying a condition based on the initial percentage of SoC in the Li-Ion BESS. This condition prioritized EV charging, starting at 20% SoC and reaching 48% SoC. By implementing this methodology, the generated energy was smoothed, providing more or less energy depending on the SoC percentage within the specified range.

The results indicate that the enhanced R-R filter method through FLC achieved a variance reduction of 14%. Figure 14 illustrates the time evolution of the resultant smoothing factor, expressed as a variable %R-R, at the output of the FLC.

Table 3. Generated power results with and without applying various proposed 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)	Utilized Life Cycles
V2GSmooth	8.54	7.35	14	9.54	9.32	0.23	1.170

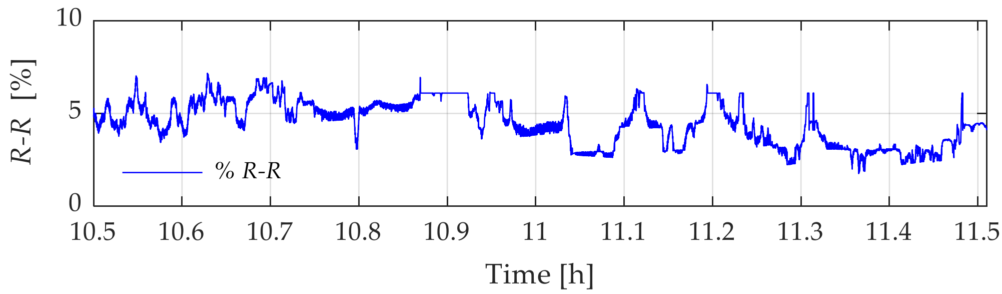

Figure 14. Real-time adjustment of the smoothing factor (%R-R).

The impact of a specific condition on the V2GSmooth method was investigated, emphasizing the prioritization of battery charging. This strategic refinement yielded a significant improvement, lowering the Utilized Life Cycles to 1.170 cycles. This result implied that proactive energy management, focusing on battery charging, can profoundly influence battery durability. Implementing this condition emerged as a promising strategy to optimize the efficiency and longevity of batteries in dynamic environments, where precise responses to electrical demand variations are crucial.

4.3. Comparison with Other Methods

In this section, based on the results presented so far, we compare the MA, R-R, and V2GSmooth methods in terms of their performance for power smoothing. The proposed method, V2GSmooth, demonstrated higher power smoothing, effectively reducing the variability of renewable power delivered to the grid. It achieves a smoother power profile, resulting in a more stable power injection to the distribution network. On the other hand, the MA and R-R methods performed better in terms of delivering energy to the system. They provided more energy, making them more advantageous in terms of power availability. However, they may have exhibited slightly less power smoothing than the V2GSmooth method. The MA and R-R methods are more straightforward to implement in software as they are based on non-complex linear algorithms. This is an advantage over the V2GSmooth method, where implementing fuzzy logic control leads to a higher computational burden during execution.

Overall, the choice between the MA, R-R, and V2GSmooth methods depends on the specific requirements and priorities of the RES-EV system. If the primary goal is to mitigate power fluctuations and ensure a consistent power output to the grid, the V2GSmooth method is highly recommended. Conversely, the MA and R-R methods may be more suitable if the emphasis is on maximizing energy delivery.

4.4. Analysis of Metrics for the Implementation of V2G with Power Smoothing Methods

This study evaluated various metrics (see Figure 15) to analyze the performance of different smoothing methods applied to power generation curves in the context of V2G. The considered metrics included standard deviation, crest factor, form factor, ripple index, and coefficient of variation. Each metric was analyzed in different scenarios using various smoothing methods on the original curve within the same time horizon.

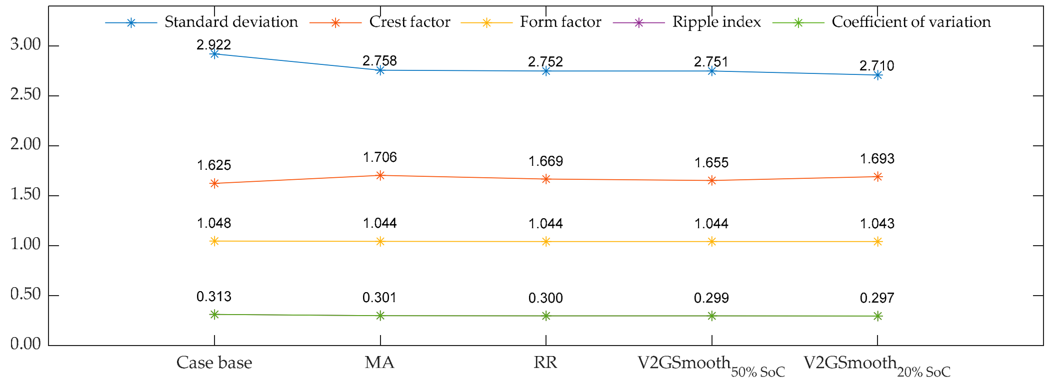

Figure 15. Power smoothing metrics analysis.

4.4.1. Standard Deviation

The standard deviation (see Figure 15), which measures the spread of data around the mean, showed a trend toward reduction with the application of smoothing methods. In particular, the ramp-rate method with a variable rate of change using fuzzy logic stood out by achieving a significant decrease in energy generation variability.

4.4.2. Crest Factor

The crest factor (see Figure 15), which evaluates the relationship between the maximum values and the square root of the mean square, did not show notable improvements with smoothing methods. All methods maintained a relatively constant prominence of peaks in energy generation.

4.4.3. Form Factor

The form factor (see Figure 15), which indicates the uniformity of the distribution, did not show appreciable improvements with smoothing methods. The distribution of energy generation remained relatively constant in all scenarios.

4.4.4. Ripple Index

The ripple index (see Figure 15), which measures the signal variation relative to the mean, experienced a reduction with smoothing methods. Specifically, the V2GSmooth method proved to be effective in providing smoother and more stable energy generation.

4.4.5. Coefficient of Variation

The coefficient of variation (see Figure 15), which evaluates relative variability to the mean, also showed a general decrease with smoothing methods. Again, the ramp-rate method with a variable rate of change using fuzzy logic stood out by providing greater relative consistency in energy generation.

In summary, the metrics analysis suggests that the V2GSmooth method can be considered the most effective option for smoothing energy generation in the context of V2G. This method reduces variability, improves stability, and offers more consistent energy generation compared to the other evaluated methods.

5. Conclusions

This paper addresses the challenges faced by insular power systems in achieving self-sufficiency and environmental sustainability through integrating renewable energy sources and the widespread adoption of electric vehicles. The geographical isolation of islands necessitates a shift from conventional energy sources to unconventional, intermittent renewables such as solar and wind energy. However, the inherent variability of these sources poses technical challenges to the stability of insular power grids, exacerbated by the increasing penetration of electric vehicles.

The innovative power smoothing technique proposed in this study, utilizing an enhanced version of the "ramp-rate" method with fuzzy logic control, demonstrates promising results in mitigating the impact of renewable energy fluctuations on the grid. Integrating electric vehicle batteries during charging, mainly through the V2G system, is a valuable resource in enhancing grid performance and stability. The experimental validation conducted in the Micro-Grid Laboratory at the University of Cuenca, Ecuador, showcases the effectiveness of the proposed method in a real-world isolated microgrid utility.

The case studies presented in this paper provide a comprehensive evaluation of the proposed power smoothing enhancement under various operational conditions. The results highlight the method's adaptability to different SoC values of the Li-Ion BESS, demonstrating its effectiveness in maintaining the operation within safe SoC values (20–80%). The proposed method significantly reduces power variance, indicating its capability to smooth out fluctuations in renewable energy generation.

Furthermore, the prioritization of the electric vehicle charging station (EVCS) in the second case study demonstrates the versatility of the proposed method in addressing specific operational objectives. The results indicate a substantial reduction in power variance and highlight the potential of the enhanced V2GSmooth method in optimizing EVCS, achieving high power stabilization effectiveness while preserving an adequate SoC of EV batteries for future usage and overall system reliability.

The comparative analysis with conventional power smoothing methods (MA and R-R) suggests that the proposed method balances power smoothing and energy delivery. While the MA and R-R methods outperform in energy delivery, the enhanced V2GSmooth method provides a more stable power profile. The choice between these methods depends on the specific requirements and priorities of the renewable energy-electric vehicle system.

Finally, the evaluation of various metrics, including standard deviation, crest factor, form factor, ripple index, and coefficient of variation, supports the superiority of the proposed method in smoothing energy generation within the context of V2G. The V2GSmooth method consistently demonstrates a significant reduction in variability, improved stability, and more consistent energy generation compared to alternative methods. However, while our study has shed light on the immediate technical and operational benefits of implementing the V2G concept using BEV batteries, it is imperative to highlight the necessity of a more extensive and comprehensive examination. Specifically, a thorough investigation into the long-term effects of BEV aging and remuneration policies for EV owners is crucial. Successfully implementing any V2G strategy hinges on a deeper understanding of how these factors evolve over an extended period. Therefore, we strongly advocate for future research endeavors that delve into the multifaceted impacts of BEV aging and associated compensation policies, providing invaluable insight for the sustainable integration of V2G technologies.

In summary, the proposed power smoothing technique, leveraging electric vehicle batteries and incorporating fuzzy logic control, presents a promising solution for insular power systems seeking to overcome the challenges associated with renewable energy integration and electric vehicle adoption. The findings of this study contribute not only to the immediate benefits of power smoothing supported on BEV but also emphasize the necessity of long-term considerations for a holistic understanding, thereby advancing sustainable and resilient energy systems for isolated regions.

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