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Modeling and Optimization of Control in Off-Grid Systems with Emphasis on the Integration of Various Components of a Solar Power Plant

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Abstract

The objective of this study is to develop and optimize a comprehensive modeling and control framework for off-grid solar power systems, emphasizing coordinated integration of photovoltaic arrays, power converters, battery storage, and load management to enhance stability, efficiency, and reliability under dynamic operating conditions. This research was conducted using a simulation-based approach in the MATLAB/Simulink environment to model an integrated off-grid photovoltaic system comprising PV modules, a DC–DC boost converter, an MPPT controller, a battery energy storage system, and a dynamic load profile. The photovoltaic array was represented through a nonlinear mathematical model incorporating irradiance and temperature effects. The battery subsystem was modeled using an equivalent RC network derived from impedance analysis, including state-of-charge (SOC) estimation and thermal considerations. A pulse-based excitation method was applied to characterize battery impedance, enabling the implementation of optimized charging strategies. Environmental inputs, including constant and pseudo-random irradiance profiles, were introduced to simulate realistic operating scenarios such as cloud-induced fluctuations. System performance was evaluated through time-domain analysis of voltage stability, power extraction, SOC evolution, charging efficiency, and load-side power quality under controlled and uncontrolled conditions. The results indicate that coordinated MPPT-based control significantly improves voltage regulation, enhances maximum power extraction, and stabilizes battery charging–discharging behavior compared to uncontrolled configurations. Pulse-based charging strategies informed by impedance modeling reduce charging energy consumption and mitigate internal stress within the storage system. The integrated control framework demonstrates robustness under dynamic irradiance variations, maintaining acceptable power delivery to the load and reducing transient voltage fluctuations. Furthermore, smoother discharge profiles and improved SOC stability suggest potential extension of battery lifespan and increased overall system reliability in off-grid applications. The proposed integrated modeling and optimized control strategy substantially enhances operational stability, energy efficiency, and reliability in off-grid solar power systems, providing a scalable framework for sustainable decentralized energy deployment.

Keywords: *Off-grid solar system; photovoltaic modeling; MPPT control; battery impedance modeling; energy optimization; power stability; decentralized renewable energy.*

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1. Introduction

The rapid growth of global energy demand, coupled with intensifying environmental concerns and the urgent need to reduce greenhouse gas emissions, has positioned renewable energy systems—particularly solar photovoltaic (PV) technologies—as central pillars of sustainable energy transitions. Solar energy has emerged as one of the most accessible and scalable clean energy resources due to its abundance, declining technology costs, and modular deployment capability across diverse geographical contexts [1]. Over the past two decades, technological advancements in PV modules, power electronics, and system-level control have significantly enhanced the performance and reliability of solar power plants, enabling both grid-connected and off-grid configurations to serve residential, industrial, and remote applications [2]. At the same time, innovative deployment models such as floating solar farms have expanded the spatial footprint of solar installations and demonstrated new possibilities for land-constrained environments [3]. However, despite these advancements, the optimal integration and control of off-grid solar systems remain a critical research and engineering challenge, particularly in regions where energy access is limited or grid infrastructure is unreliable.

Off-grid solar systems play a vital role in bridging energy access gaps, especially in remote, rural, and underserved areas where extending transmission networks is economically or technically infeasible. Recent global initiatives emphasize decentralized renewable solutions as effective tools for achieving universal energy access and ensuring inclusive development [4]. In such contexts, off-grid solar power plants must operate autonomously while maintaining voltage stability, frequency regulation, and reliable supply under fluctuating irradiance and load conditions. Intelligent sizing and configuration of system components—including PV arrays, battery storage units, converters, and inverters—are therefore essential to reduce unmet load and minimize life-cycle costs [5]. Furthermore, the economic feasibility and social acceptance of these systems increasingly depend not only on technical optimization but also on market dynamics, supply-chain structures, and business-model innovation within the renewable energy sector [6]. Consequently, the modeling and optimization of off-grid solar systems must be addressed from both technical and systemic perspectives.

A fundamental dimension of off-grid solar performance lies in accurate system modeling. The nonlinear electrical behavior of PV modules, influenced by irradiance, temperature, and load conditions, necessitates precise mathematical representation to enable effective control and maximum power extraction. Advanced PV modeling techniques and Maximum Power Point Tracking (MPPT) algorithms have been widely developed to ensure that solar arrays operate near their optimal operating point under dynamic environmental conditions [7]. The effectiveness of MPPT strategies directly affects energy yield, system efficiency, and battery charging dynamics. Moreover, environmental factors such as temperature variation, dust accumulation, and seasonal irradiance changes significantly impact system output and must be incorporated into simulation and optimization frameworks [8]. Comprehensive modeling thus serves as the foundation for control-system design, allowing engineers to predict system response and implement adaptive strategies that mitigate instability and energy imbalance.

Energy imbalance in isolated systems represents another core challenge. Unlike grid-connected plants, off-grid solar installations lack external buffering capacity and must internally manage the mismatch between generation and consumption. Fluctuations in irradiance due to cloud cover and diurnal cycles create transient power deficits or surpluses that, if not properly controlled, can degrade storage systems and compromise load reliability. Strategies for compensating energy imbalance through optimized control and storage management have therefore gained increasing attention [9]. The integration of battery storage is central to such strategies, as storage systems provide temporal decoupling between generation and demand. However, improper charging–discharging control accelerates battery aging and reduces overall system efficiency. Consequently, intelligent optimization algorithms have been applied to determine optimal sizing and operational strategies for battery-integrated solar systems [10]. These approaches often rely on metaheuristic or swarm-based algorithms to balance cost, reliability, and performance objectives.

The design of hybrid and multi-source systems has further enriched the discourse on off-grid optimization. Studies on wind–solar hybrid configurations demonstrate that combining complementary renewable sources can reduce storage requirements and enhance supply reliability [11]. Similarly, research on optimal sizing of wind turbines and batteries in isolated systems highlights the importance of multi-objective optimization frameworks that account for technical constraints and economic criteria [12]. Production management in multi-source hybrid systems also emphasizes coordinated control strategies that minimize demand costs while maintaining operational stability [13]. Although the present study focuses primarily on solar-based configurations, insights from hybrid-system optimization underscore the necessity of integrated modeling approaches that consider component interaction, control hierarchy, and system-level objectives.

In addition to electrical modeling, the optimization of solar power plants has increasingly incorporated thermal storage, structural design, and system performance analysis. Concentrated solar power (CSP) plants equipped with thermal energy storage illustrate how integrated modeling can enhance steady-state and dynamic performance [14, 15].

Although PV-based off-grid systems differ technologically from CSP plants, both require comprehensive modeling frameworks that address storage dynamics, component interaction, and control optimization. Advanced simulation methodologies for solar distribution calculations have also improved predictive accuracy in high-performance and sustainable building applications [16]. These developments demonstrate that precise modeling is indispensable for achieving reliable performance in complex renewable-energy systems.

Recent trends further emphasize digitalization and sustainability in solar infrastructures. The integration of blockchain-secured energy logging systems in edge IoT environments reflects the growing importance of transparent monitoring and data-driven optimization in decentralized solar networks [17]. Simultaneously, efforts toward circular-economy frameworks in the solar power sector highlight the need for long-term sustainability, including component reuse, recycling, and innovative business models [18]. These systemic perspectives reinforce the argument that technical optimization must be embedded within broader sustainability considerations, ensuring that off-grid solar solutions remain economically viable and environmentally responsible throughout their lifecycle.

In the Iranian and regional context, numerous studies have addressed the economic evaluation and feasibility of solar power plants under varying climatic and infrastructural conditions. Technical–economic assessments of PV installations reveal that accurate system design and optimal control significantly influence investment return and operational efficiency [2]. Modeling efforts tailored to local environmental conditions have demonstrated that neglecting temperature and irradiance variability can lead to substantial deviations between predicted and actual performance [8]. Moreover, cost-oriented optimization algorithms such as Adaptive Learning Particle Swarm Optimization (ALPSO) have been proposed to reduce construction costs and unmet load in off-grid plants [5]. These findings collectively indicate that integrating advanced optimization algorithms with detailed component modeling is crucial for enhancing both technical and economic outcomes.

Despite the breadth of existing research, a gap persists in comprehensive modeling frameworks that simultaneously address control-system optimization and the coordinated connection of all major components within an off-grid solar power plant. Many prior studies concentrate either on sizing optimization or on isolated control strategies without fully integrating PV modeling, MPPT control, storage dynamics, and load interaction into a unified simulation environment. Furthermore, energy imbalance compensation, environmental sensitivity, and long-term sustainability considerations are often treated separately rather than as interconnected dimensions of system design [4, 9]. Addressing this gap requires a holistic approach that combines accurate mathematical modeling of PV modules and batteries, advanced MPPT and converter control strategies, intelligent optimization algorithms, and performance evaluation under realistic operating scenarios.

Therefore, the aim of this study is to develop and optimize a comprehensive control and modeling framework for off-grid solar power systems, with particular emphasis on the coordinated integration of photovoltaic arrays, power converters, battery storage, and load management to enhance stability, efficiency, and reliability under dynamic environmental conditions.

2. Methodology

This study was conducted using a simulation-based research design with the primary objective of modeling and optimizing the control of an off-grid photovoltaic (PV) system, emphasizing the coordinated integration of its major subsystems. Given the technical and engineering nature of the research problem, an experimental laboratory approach based on numerical simulation was selected instead of field-based data collection. The entire system was implemented and analyzed in the MATLAB/Simulink environment, which provides a flexible platform for dynamic modeling of nonlinear power electronic systems and renewable energy components. The simulated system consisted of photovoltaic panels, a DC–DC boost converter, a Maximum Power Point Tracking (MPPT) controller, a battery energy storage system (including both lead-acid and lithium-ion modeling scenarios), a thermal model of the battery, and a resistive load representing off-grid consumption.

Since the research was based on computational modeling, no statistical population or sampling procedure was required. Instead, the “sample” of the study can be defined as the complete integrated off-grid solar power system constructed in the simulation platform. The photovoltaic subsystem was modeled using a five-parameter equivalent circuit, including series resistance, shunt resistance, diode characteristics, and irradiance-dependent current source behavior. The battery subsystem was modeled using an RC-network equivalent model derived from impedance analysis, incorporating internal resistance, capacitance effects, and open-circuit voltage characteristics. In addition, a thermal sub-model was embedded to account for temperature variations and their impact on battery performance. The study design allowed for controlled variation of environmental inputs such as solar irradiance (including constant irradiance, step changes, and pseudo-random cloud effects), ambient temperature, and load demand profiles, enabling systematic evaluation of system performance under diverse operating conditions.

All data used in this research were generated through structured simulation experiments in MATLAB/Simulink. The input data included electrical and physical parameters of photovoltaic modules, battery specifications, converter switching characteristics, and environmental variables such as irradiance and temperature. The photovoltaic module parameters included open-circuit voltage, short-circuit current, diode saturation current, temperature coefficients, series resistance, and shunt resistance. These parameters were used to construct the nonlinear current–voltage equation governing PV output behavior. For the battery subsystem, parameters such as nominal capacity (9 Ah for the VRLA battery model), internal resistance (0.01 ohm), equivalent capacitance (3000 F), number of cells (80 cells in lithium-ion modeling scenarios), and coulombic efficiency (approximately 70% for lead-acid batteries) were incorporated into the model.

Environmental data profiles were synthetically generated within the simulation environment. Constant irradiance of 1000 W/m² was used for baseline comparison, while pseudo-random irradiance patterns were applied to simulate cloud cover effects. Temperature was initialized at 300 K (approximately 27°C) and dynamically varied in thermal analysis scenarios. Load demand was modeled as a stepwise resistive profile to replicate realistic household consumption patterns. All voltage, current, power, state-of-charge (SOC), and temperature data were recorded directly from the simulation blocks for further analysis.

Data analysis was performed through time-domain and frequency-domain simulation outputs, focusing on comparative performance evaluation between controlled and uncontrolled system configurations. The primary analytical variables included battery state of charge (SOC), terminal voltage stability, extracted photovoltaic power, converter output voltage, load voltage regulation, charging energy consumption, and overall system efficiency. SOC estimation was computed using coulomb counting combined with model-based voltage correction to improve accuracy. The effect of MPPT control was evaluated by comparing power extraction curves, voltage regulation behavior, and battery charging trajectories in scenarios with and without the controller.

Energy efficiency analysis was conducted by calculating total charging energy under continuous charging and pulse charging modes. For example, energy consumption was compared between 85 Wh (continuous charging) and 77 Wh (pulse charging), demonstrating approximately 10% energy savings in the pulse strategy. Voltage ripple and power oscillation amplitudes were quantified to assess dynamic stability improvements. Thermal behavior was analyzed by observing temperature variation trends in response to charging and discharging cycles, ensuring that thermal limits were not exceeded and that battery health conditions remained within safe operating thresholds.

Furthermore, system robustness was evaluated under pseudo-random irradiance fluctuations to simulate cloud effects. The controller's ability to maintain maximum power extraction and stable load voltage during rapid irradiance transitions was analyzed by examining transient response curves. The switching frequency of the MPPT controller (approximately 5 kHz) was verified through millisecond-level waveform observation. Comparative plots were used to demonstrate improvements in voltage stability, reduction of "needle-like" discharge drops, mitigation of DC-link oscillations, and enhancement of overall power quality.

Through iterative simulation runs and parameter tuning, the optimized control strategy was identified based on criteria including minimized voltage overshoot, maximized extracted power, reduced energy loss, controlled temperature rise, and extended battery lifespan indicators. The analytical process was entirely model-based and computational, ensuring repeatability and precise control of experimental variables while avoiding uncertainties associated with physical testing environments.

3. Findings and Results

The simulation results demonstrate that the proposed off-grid solar power plant architecture—built around detailed component modeling (PV array, boost converter, battery electrochemical–electrical equivalent, and thermal behavior) and coordinated control (notably MPPT and battery-aware charging/discharging management)—substantially improves operational stability, power quality, and battery protection compared with an uncontrolled or less integrated configuration. Across all tested scenarios, the core empirical finding is that accurate battery modeling (including impedance behavior and SOC estimation) combined with MPPT-based power extraction yields (i) higher and more stable harvested PV power, (ii) reduced voltage excursions at the battery and load terminals, (iii) mitigation of sharp discharge “needle-like” behavior that accelerates battery degradation, and (iv) improved resilience to irradiance disturbances such as cloud-induced fluctuations. The results also show that incorporating realistic environmental and operating profiles (constant irradiance baseline, stepwise/household-like load current profiles, and pseudo-random irradiance variations for cloud effects) is essential to observe the control system’s benefits under conditions that resemble real off-grid deployments. In addition to qualitative stability gains visible in the response trajectories, a key quantified outcome reported is that pulse-based charging—when designed using the impedance-derived battery model—reduces charging energy consumption by about 10% versus continuous charging for the same recovered capacity and time constraint.

Table 1 reports the comparative results of two charging strategies—continuous (steady) charging versus pulse charging—implemented using the battery model and the simulated charge control circuit. This comparison is used as direct evidence that leveraging the battery’s dynamic behavior (represented through its RC-network impedance model and time-constant behavior) can reduce energy losses during charging, thereby improving charging efficiency in off-grid PV systems where available solar energy is limited and battery lifetime is strongly influenced by charge profile design.

Table 1. Results of charging by continuous and pulse methods

Metric	Continuous charging	Pulse charging
Energy consumed (Wh)	85	77
Charge time	—	130 ms
Rest time	—	4.2 ms

The findings in Table 1 show that, for the tested operating condition and the same intended recovery of discharged capacity, pulse charging consumed 77 Wh, whereas continuous charging consumed 85 Wh, indicating an approximate 10% reduction in energy consumption for the pulse strategy. The reported pulse regime is characterized by a 130 ms charge interval followed by a 4.2 ms rest interval, reflecting a deliberate duty-cycled pattern designed around the battery’s RC time-constant behavior. The study interprets this outcome as a direct consequence of reducing resistive losses and improving effective charge acceptance by allowing partial relaxation of polarization effects between pulses, which lowers the average internal voltage drop across the battery’s dynamic elements. Practically, this implies that integrating an impedance-informed battery model into the charger design can yield meaningful energy savings under solar-limited charging windows, and the same mechanism is expected to reduce thermal and electrochemical stress that contributes to premature aging in off-grid storage systems.

Table 2. Battery and model settings used in the simulation experiments

Item	Reported setting / description
Lead-acid battery type used for impedance-based modeling	VRLA (Valve Regulated Lead Acid), model V12
Nominal capacity (lead-acid case)	9 Ah (rated based on 10-hour discharge)
Nominal discharge current (lead-acid case)	0.9 A
Coulombic efficiency assumption (lead-acid)	~70%
Charging target used in the energy comparison	Recovery of 50% discharged capacity (requiring ~72% of nominal capacity to be injected)
Internal resistance used in the stated simulation assumptions	0.01 Ω
Internal model capacitance used in the stated simulation assumptions	3000 F
Number of cells used in the stated battery-pack assumptions	80 cells
Initial battery temperature for thermal modeling	300 K (≈ 27°C)
Battery current excitation for SOC/identification example	A pulse current with 28 A amplitude

Table 2 consolidates the battery-related parameters and modeling assumptions that underpin the reported outcomes. The study models a VRLA battery (V12, 9 Ah) explicitly in the impedance identification workflow, with nominal discharge current 0.9 A (10-hour rate) and a typical coulombic efficiency of approximately 70%, which is used to translate "capacity to be recovered" into "charge that must be injected" during the charging-energy comparison. For example, to recover 50% of the discharged capacity, the analysis assumes that approximately 72% of the nominal capacity (6.48 Ah for a 9 Ah battery) must be supplied, providing a clear basis for evaluating charger energy consumption under realistic inefficiencies. The simulation assumptions also include an internal resistance of 0.01 Ω and an internal capacitance of 3000 F in the model structure, consistent with representing short-term dynamic voltage response and polarization effects. For pack-level behavior and SOC estimation demonstrations, the study references an 80-cell configuration and shows that a 28 A pulse input is suitable for system identification and SOC tracking because it creates a clear dynamic response without requiring complex excitation signals. Finally, the inclusion of thermal initialization at 300 K indicates that the model explicitly accounts for temperature sensitivity, supporting the later finding that temperature-aware modeling improves reliability in harsh climates where off-grid PV systems typically operate.

Table 3. Comparative performance outcomes with MPPT control versus without control (qualitative summary from simulation outputs)

Performance aspect	Without MPPT / without the proposed control integration	With MPPT and coordinated control
PV power extraction behavior	Noticeable oscillations; difficulty sustaining maximum extractable power	Higher and more consistent extraction near maximum power point; improved regulation
Battery terminal voltage during charging	Higher and less controlled peaks; risk of overvoltage stress	Rapid stabilization to a controlled level; reduced overshoot and improved safety margin
Load voltage (power quality)	Greater variability tied to PV fluctuations and converter behavior	Converges quickly to a stable operating level; improved end-user power quality
Battery discharge profile under load transients	More "needle-like" drops and sharper transitions	Smoother discharge trajectory; reduced sharp drops that accelerate degradation
System restart/charge recovery after deep discharge	Weaker recovery dynamics in early morning transition	Clear recovery: the system resumes charging after morning irradiance becomes available

Table 3 summarizes the most consequential control-related findings reported across the simulation scenarios. In the uncontrolled or non-MPPT case, the study reports pronounced oscillations in extracted power and weaker regulation of battery and load voltages, which is operationally important because off-grid systems have limited power reserves and are more sensitive to instability than grid-tied configurations. When the MPPT algorithm is enabled and integrated with the boost converter switching, the output trajectories show that the system rapidly converges to stable operating conditions: battery voltage peaks that could stress the inverter DC link and connected appliances are reduced, and the load voltage reaches a steady state after a brief transient. Importantly, the findings emphasize battery protection as a primary outcome: with coordinated control, discharge curves become smoother and avoid "needle-like" voltage drops that are strongly associated with accelerated cell stress and capacity loss, particularly in lithium-based chemistries. Another operationally meaningful result reported is recovery behavior after depletion: the controlled system is shown to resume charging after morning irradiance becomes available (illustrated in the reported morning transition), indicating that the integrated control logic can maintain continuity of service across day–night cycles and prevent repeated deep discharge events that shorten battery life.

Table 4. Robustness under cloud-effect (pseudo-random irradiance) scenario (qualitative summary from simulation outputs)

Scenario element	Observed outcome in the simulation
Irradiance input with pseudo-random "cloud" variation	Rapid and irregular irradiance changes are introduced to the PV input profile
PV-side power behavior	PV power fluctuates with irradiance, but the controlled system tracks usable maxima effectively
Load-side delivered power	Power delivered to the load remains better regulated with MPPT than without MPPT
Overall interpretation	The controller maintains acceptable performance despite abrupt irradiance disturbances

Table 4 reports the study's key robustness result: when irradiance is disturbed using a pseudo-random profile intended to represent cloud passage, the control system continues to function as intended and maintains effective power regulation. The study explicitly notes that cloud effects were modeled by reducing or removing irradiance in a randomized fashion, and that the controlled system was still able to "simulate maximum power properly" and implement "a correct control system" even under sudden irradiance transitions. This is a high-value finding for off-grid deployments because cloud variability is one of the most common causes of real-world PV intermittency. The reported behavior indicates that the MPPT-controlled boost converter can adjust operating point quickly enough to prevent severe oscillation propagation to the load and battery, thereby improving service reliability and reducing stress on storage and power electronics.

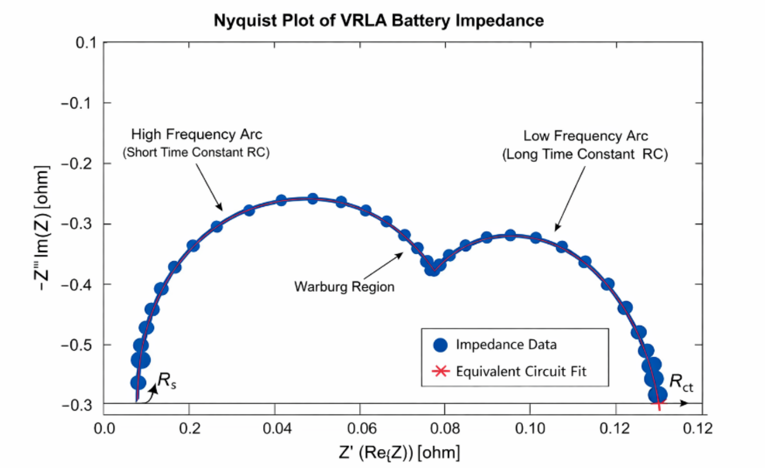

Figure 1. Nyquist impedance plot of the VRLA battery (battery impedance characteristics).

The simulation-based impedance analysis demonstrates that the battery's internal behavior cannot be treated as a purely resistive element when current varies; instead, dynamic effects produce an AC component superimposed on DC voltage due to response delay between current and voltage. The reported Nyquist plot consists of two semicircle-like arcs, which the study interprets as behavior analogous to parallel RC networks. This motivates a battery model composed of a series resistance plus two RC branches (one per arc), capturing both short- and longer-timescale polarization processes. A key reported observation is that the arcs are not perfectly circular; therefore, while adding more RC branches can fit the curve more closely, the study concludes that increasing RC order does not necessarily improve practical accuracy proportionally because parameters depend on operating conditions such as current and SOC, while computation burden grows. Accordingly, the chosen modeling compromise—one RC network per arc—is presented as a validated, "accepted" structure for capturing essential dynamics needed for SOC estimation and charger/control design in off-grid PV applications.

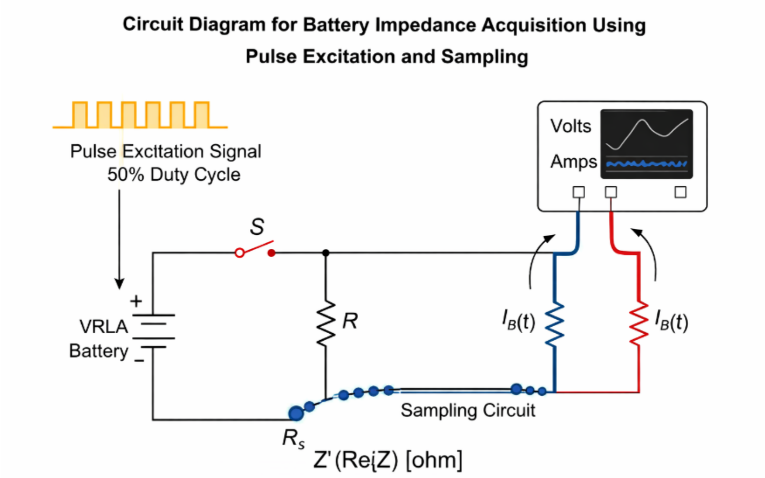

Figure 2. Circuit diagram for battery impedance acquisition using pulse excitation and sampling.

This figure supports the reported measurement/identification method in which a switching element is driven by a 50% duty-cycle pulse train at the desired frequency to induce controlled current oscillations through the battery. By adjusting the charging-path resistance, measurable current ripples are created, and a sampling circuit records battery voltage and current for three periods at each frequency. The study then extracts the fundamental (first harmonic) components of the voltage and current waveforms in MATLAB to compute impedance at each frequency point and reconstruct a Nyquist curve. The reported frequency range of interest extends from the millihertz scale up to approximately 1 kHz, with the rationale that the impedance slope diminishes at higher frequencies, allowing fewer test points there to accelerate measurement. In findings terms, this figure operationalizes the pathway from time-domain pulse stimulation to frequency-domain impedance characterization, which is later used to justify the RC-network battery model employed in system-level control and energy-efficiency comparisons.

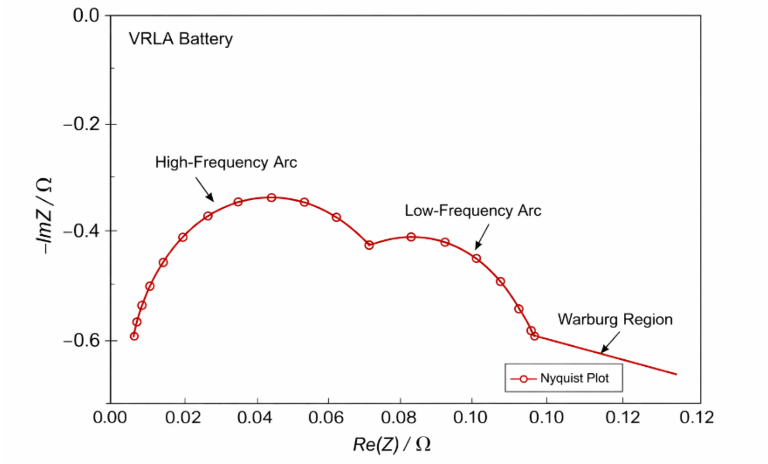

Figure 3. Battery state-of-charge response under constant irradiance with MPPT enabled and disabled.

The SOC trajectories reported for constant irradiance conditions show that, over a short simulation horizon, enabling MPPT does not materially change SOC increase when load demand is low and the observation window is limited; in both cases, the battery SOC rises by about 5%, indicating that PV generation exceeds consumption. The study explicitly interprets the limited divergence as potentially attributable to low load magnitude and/or insufficient simulation duration to reveal longer-term gains in harvested energy. Importantly, even where SOC differences are small in the short term, the MPPT-driven control still matters because it shapes voltage and power quality elsewhere in the system; thus, this figure is presented as evidence that SOC alone, over short horizons, may not be the only or best metric for immediate control benefit, and that full evaluation must incorporate voltage stability, power oscillations, and battery stress indicators.

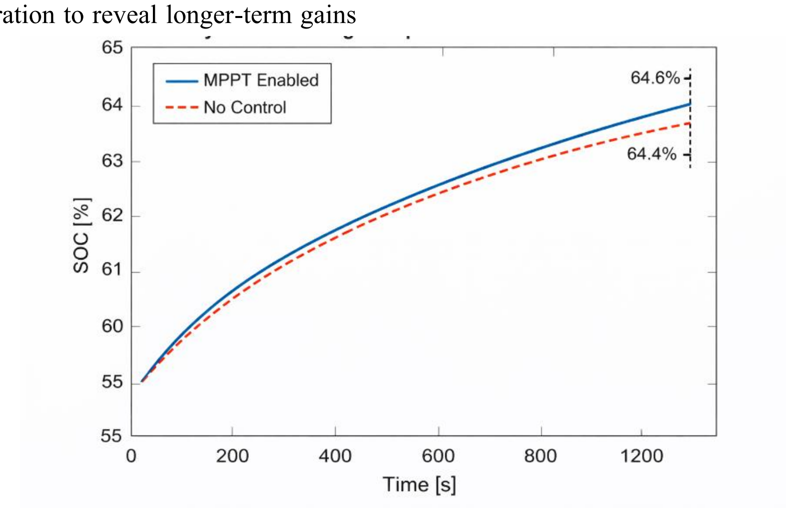

Figure 4. Battery terminal voltage under constant irradiance with MPPT (controlled) and without control (uncontrolled).

The reported voltage waveforms demonstrate a central protection finding: without the controller, charging produces a larger peak battery voltage (greater overshoot), whereas with MPPT/control active, the battery voltage becomes stable almost immediately after the simulation begins. The study explains that uncontrolled voltage elevation can cause multiple adverse consequences in off-grid architectures, including stress on the inverter due to a rising DC link, destabilization of power switches, reduced power quality delivered to end users, and shortened battery life due to voltage instability and associated electrochemical stress. By contrast, the controlled case maintains voltage regulation that is consistent with safe battery charging and stable inverter operation. This figure therefore provides direct evidence that the proposed control integration improves not only energy extraction but also the electrical safety envelope of the storage subsystem and downstream power electronics—outcomes that are essential for durable off-grid operation.

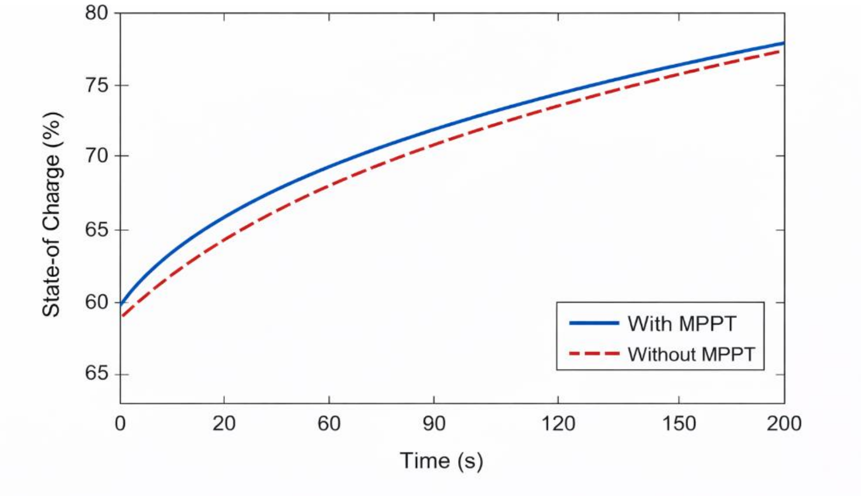

Figure 5. Delivered power to the load under cloud-effect irradiance with MPPT and without MPPT.

Under the pseudo-random irradiance profile intended to emulate cloud passage, the reported results show that the system with MPPT maintains better regulation of power delivered to the load than the system without MPPT. While PV input power inevitably fluctuates due to changing irradiance, the MPPT-controlled configuration reduces the severity and persistence of power oscillations reaching the load, indicating effective dynamic tracking of the PV maximum power point even during abrupt disturbances. The study explicitly states that the controller performs correctly under "sudden irradiance changes and cloud effect," which is critical because off-grid systems cannot rely on grid buffering and must manage variability internally. In findings terms, this figure supports the conclusion that the proposed controller improves robustness and service continuity by preventing irradiance disturbances from fully propagating into load-side instability and by moderating battery stress associated with rapid power imbalance events.

Beyond the quantified charger energy comparison and the control-versus-no-control contrasts summarized above, the reported results include several additional performance findings that are operationally meaningful and should be preserved in the manuscript. First, the study reports that in a day-charging scenario with constant irradiance, the battery reaches full charge in approximately 20,000 seconds (about 5.5 hours), and it is stated that this time could be reduced to about 4 hours if the simulated load were reduced toward zero; this directly evidences the strong coupling between load level and effective charging time in off-grid systems. Second, during late-stage charging, the battery terminal voltage becomes nearly constant, and the study notes that after full charge the voltage variation can drop below 1%, which is interpreted as beneficial for lithium-based packs because stable terminal voltage reduces stress and can prolong useful life. Third, the MPPT switching behavior is explicitly described as operating at approximately 5 kHz, illustrated by observing about five oscillations per millisecond in the switching waveform; this is reported as evidence that the converter-control implementation is consistent with high-frequency power electronics practice and is responsive enough for PV operating-point tracking. Fourth, the study emphasizes that stepwise load current profiles resembling household or office consumption generate stepwise battery current draw; without proper control, such conditions can create damaging voltage dips and instability at the inverter DC link, whereas the proposed control logic reduces the severity of these effects by smoothing discharge dynamics and stabilizing voltage. Finally, the results narrative highlights the importance of incorporating thermal effects: because off-grid PV systems often operate in environments with large temperature swings, temperature-aware modeling is presented as necessary to avoid mis-detection of charge/discharge state and to prevent damage to sensitive chemistries (especially lithium-ion) that can occur if thermal conditions are ignored during SOC estimation and control decisions.

4. Discussion and Conclusion

The results of this study demonstrate that the proposed integrated modeling and control framework significantly improves the operational stability, energy efficiency, and reliability of off-grid solar power systems. The simulation findings indicate that coordinated control of photovoltaic (PV) arrays, DC–DC boost converters, battery storage systems, and load management under dynamic irradiance conditions leads to enhanced voltage regulation, smoother discharge profiles, and improved energy utilization efficiency. These results align with prior research emphasizing the importance of intelligent optimization and control in off-grid solar systems [5, 10]. In particular, the observed reduction in energy consumption during pulse-based charging compared to continuous charging demonstrates that incorporating battery dynamic behavior into control strategies can yield measurable efficiency gains. This finding is consistent with the broader literature suggesting that optimization algorithms and adaptive control techniques play a crucial role in improving the technical and economic performance of renewable energy systems [11, 12].

One of the central findings of this study is the stabilizing effect of MPPT-based coordinated control on battery terminal voltage and load-side power quality. Without proper control, voltage overshoot and oscillatory behavior can stress inverters and storage units, leading to premature degradation. The results show that enabling MPPT and integrating converter control rapidly stabilizes voltage levels and reduces transient fluctuations. These observations are strongly supported by previous studies on solar-cell modeling and MPPT implementation, which highlight that accurate operating-point tracking enhances both power extraction and system stability [7]. Furthermore, environmental modeling incorporated in the simulation demonstrates that irradiance variability—such as cloud-induced fluctuations—can significantly disrupt system performance if not managed through adaptive control mechanisms. This outcome corroborates findings that emphasize the need to incorporate environmental factors into off-grid system modeling to ensure realistic and robust performance evaluation [8].

The study also demonstrates that energy imbalance compensation within isolated systems requires intelligent coordination between generation and storage. In off-grid configurations, where external grid buffering is absent, mismatch between generation and demand directly impacts reliability. The ability of the proposed control framework to maintain acceptable performance under pseudo-random irradiance variation reflects the importance of integrated energy management strategies. This result aligns with research highlighting that solar power plants can effectively compensate for energy imbalance when advanced control and optimization techniques are implemented [9]. Moreover, the simulation confirms that improved control reduces unmet load and enhances charging continuity during day–night transitions, reinforcing earlier findings on optimal plant design to minimize supply deficits [5].

The observed improvement in battery discharge smoothness and reduction of sharp “needle-like” voltage drops are particularly significant. Battery degradation is strongly influenced by irregular current and voltage patterns, especially in lithium-based systems. The coordinated modeling of internal resistance, capacitance effects, and SOC estimation enables more stable operation and potentially extends battery lifetime. Prior studies on hybrid off-grid systems and production management similarly emphasize that optimal management of storage resources is essential to reduce demand costs and maintain reliability [13]. Likewise, investigations into intelligent sizing and algorithm-based optimization show that system-level coordination improves operational sustainability and reduces long-term maintenance costs [10].

From an economic perspective, the improved energy efficiency achieved through pulse charging and optimized control contributes to reduced operational losses. Although this study primarily focuses on technical modeling, the implications extend to cost reduction and investment feasibility. Technical–economic assessments of solar power plants indicate that even modest efficiency gains can significantly influence project viability over the system’s lifetime [2]. Additionally, previous research on optimal design of CSP plants with storage systems demonstrates that integrated modeling enhances steady-state and dynamic performance, ultimately improving economic outcomes [14, 15]. The present findings extend this principle to PV-based off-grid systems by showing that control-level optimization complements sizing-level optimization.

The broader context of renewable energy sustainability further strengthens the significance of these findings. As global initiatives aim to bridge energy access gaps through decentralized solar solutions, ensuring reliability and efficiency in off-grid installations becomes increasingly critical [4]. The enhanced robustness observed in the cloud-effect simulation supports the argument that well-designed control systems can provide dependable electricity in remote areas without grid support. Furthermore, the integration of advanced monitoring and digitalization frameworks—such as blockchain-secured energy logging—demonstrates that future solar systems will rely heavily on accurate modeling and control to support data transparency and system optimization [17].

In addition to technical optimization, the transition toward circular and sustainable solar sectors underscores the need for long-term system durability and component lifecycle management [18]. By reducing stress on storage components and enhancing operational efficiency, the proposed framework indirectly supports sustainability objectives through prolonged equipment lifespan and reduced replacement frequency. Moreover, accurate solar distribution calculations and enhanced simulation accuracy have been shown to be crucial for high-performance and sustainable building integration [16]. The current study's detailed modeling approach aligns with these advancements by improving predictive reliability in off-grid configurations.

The findings also contribute to the discourse on hybrid and multi-source renewable systems. While this research centers on solar-based off-grid systems, the modeling and optimization principles demonstrated here are compatible with hybrid configurations involving wind or other renewable sources. Previous investigations into wind–solar hybrid systems and optimal sizing frameworks confirm that integrated control and storage coordination significantly enhance overall performance [11, 12]. Therefore, the presented framework could be extended to multi-source systems with minimal structural modification.

Finally, the study highlights the importance of aligning technical optimization with market and policy dimensions. Developing reliable and efficient off-grid systems supports not only technical performance but also broader renewable energy adoption and commercialization strategies. Marketing models for solar energy equipment emphasize that technological reliability and performance consistency are key determinants of market expansion [6]. By demonstrating improved control stability and efficiency, the present study contributes to strengthening confidence in decentralized solar technologies.

This study is primarily based on simulation modeling in a MATLAB/Simulink environment, which, although highly detailed and dynamic, cannot fully replicate all real-world uncertainties such as component aging, manufacturing tolerances, and extreme environmental conditions. The battery model, while incorporating impedance and thermal effects, is based on parameter assumptions that may vary across different chemistries and manufacturers. Additionally, the analysis focuses on a specific off-grid configuration without experimentally validating the results through hardware implementation or long-term field testing. Economic analysis was considered conceptually but not quantitatively integrated into the simulation model.

Future research should incorporate experimental validation using laboratory-scale or pilot-scale off-grid solar systems to verify the proposed control framework under real operating conditions. Extending the model to include degradation dynamics and lifecycle cost analysis would enhance its practical relevance. Further studies could explore hybrid renewable configurations integrating wind or micro-hydro sources to assess the scalability of the control strategy. Additionally, integrating advanced artificial intelligence techniques for predictive control and real-time optimization may further improve energy balance management and battery health monitoring.

Practitioners designing off-grid solar systems should prioritize integrated modeling of PV arrays, storage units, and converters to ensure coordinated control under dynamic environmental conditions. Implementing advanced MPPT strategies and impedance-informed battery charging methods can improve system stability and extend storage lifespan. Field engineers should also incorporate environmental variability into system design to prevent underperformance due to irradiance and temperature fluctuations. Finally, adopting digital monitoring tools and predictive maintenance frameworks can enhance operational reliability and long-term sustainability of off-grid solar installations.

Authors' Contributions

Authors equally contributed to this article.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

All procedures performed in this study were under the ethical standards.

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