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Grid Efficiency and Power Quality Improvements in Rooftop Solar EV Charging Stations Using Smart Battery Management and Advanced DC-to-DC Converters

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Abstract

The adoption of electric vehicles (EVs) is a promising strategy for reducing emissions and promoting sustainable mobility. The increasing adoption of EVs has created a demand for efficient and sustainable charging infrastructure. The integration of rooftop solar-powered EV charging stations into distribution networks is a promising solution for reducing carbon emissions and improving grid efficiency. This integration also introduces challenges, such as power quality issues, grid instability, and the impact of environmental factors on solar generation. This study proposes a novel system that integrates a smart control algorithm for a central battery management system (CBMS) with advanced bidirectional DC-DC converters for optimised power distribution. Unlike existing systems that focus on individual components, this study combines real-time environmental monitoring with adaptive power management algorithms to handle variations in generation owing to solar irradiance, temperature, and shading, and ensure maximum power harvesting. This study also presents the role of the DC-to-DC converter integrated with a smart charging control and CBMS in smart grid-enabled EV charging station. The proposed system was validated using MATLAB 2025b Simulink simulations. This study demonstrates an improvement in overall grid stability and highlights the potential of DC-DC converter technologies for smart grid applications and decarbonisation efforts.

Keywords: advanced DC-to-DC converter; centralised battery management system (CBMS); IoT-based control algorithm; energy storage system (ESS); electric vehicles (EVs)

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1. Introduction

One of the major challenges facing the world today is air pollution caused by the increasing levels of greenhouse gases in the atmosphere. The global transition to EVs is a critical strategy for reducing greenhouse gas emissions and promoting sustainable transportation. According to the International Energy Agency, EV sales reached 14 million units in 2023, necessitating a robust charging infrastructure [1]. Rooftop solar-powered EV charging stations present a promising solution for renewable energy to meet the growing demand for EV charging while reducing dependence on traditional fuel-based grids. However, integrating these systems into distribution networks introduces challenges that include power quality degradation, grid instability, and variability in solar generation due to environmental factors [2]. Existing EV charging infrastructures are classified into three distinct types: grid-connected chargers, standalone solar chargers, and hybrid systems [3].

Grid-connected systems often increase peak load demands, leading to voltage fluctuations and harmonic distortions. Standalone solar chargers, while sustainable, suffer from intermittency and limited scalability. Hybrid systems combining solar power and an energy storge system (ESS) show promise but require sophisticated management to optimise power flow and maintain grid stability [4]. Despite advancements in present systems, there is a lack of real-time environmental adaptability and efficient power conversion. Environmental factors, such as solar irradiance, temperature, and shading, significantly impact solar generation; yet, most systems rely on static models that fail to account for dynamic conditions [5]. Moreover, conventional DC-DC converters used in these systems often operate inefficiently under varying load conditions, resulting in increased power losses and reduced system reliability. To solve these challenges, there is a need for intelligent control systems that integrate IoT-based monitoring, advanced control algorithms, and high-efficiency power electronics to ensure a stable, scalable, and sustainable EV charging infrastructure [6]. In this study, to address the intermittency of solar power generation and ensure continuous power supply, an intelligent energy system integrating solar and a battery backup-based EV charging station was designed to fulfil the load demand at peak hours and store a fixed amount of energy in the battery for EV charging. The proposed smart energy management system plays a vital role in managing the intermittency of renewable energy sources. This study also includes how environmental factors affect solar generation using a previous case study analysis from Auckland, New Zealand, utilising the real-time data of solar radiation, temperature and wind speed of various months to check the feasibility and power generation capacity.

1.1. Recent Trends in RES-Integrated Modern Grids

1. Bokopane et al. [7] focused on optimising electric vehicle charging station (EVCS) operations to maximise renewable energy utilisation, minimise battery and grid energy usage, and promote coordinated charging dispatch. A hierarchical charging scheme prioritises modes based on the available renewable generation, battery state-of-charge, and user demand. The simulation of a hybrid energy system under daily variable weather and load profiles reflects real-world conditions and reduces modelling uncertainty. They also pointed out some challenges, such as grid instability and infrastructure strain arising from uneven EVCS distribution and existing electricity constraints (e.g., in South Africa), posing risks to EV adoption and grid stability. High and uncoordinated EV charging can overload distribution networks and disrupt building energy systems, and standalone EVCSs face additional limitations, including resource variability, site accessibility, long charging times, insufficient peak capacity, and battery health degradation.
2. Priya et al. [8] examined the challenges associated with the incorporation of renewable energy sources (RESs) into the grid. The unpredictable nature of power generation from these sources has an adverse impact on grid frequency and voltage. Additionally, reverse power flow issues may arise in distribution systems. High installation and maintenance costs further limit the widespread adoption of these technologies. To address these challenges, the implementation of advanced algorithms with real-time forecasting capabilities, enabled by the IoT, is necessary for accurate generation prediction. The use of smart grids with local control mechanisms can enhance the stability and reliability of the grid. Moreover, hybrid systems that combine solar, wind, and battery storage can significantly improve overall system stability.
3. Kiasari et al. [9] explored the challenges associated with battery storage systems, particularly the degraded battery performance over time, which adversely affects the reliability of the overall system. This degradation can lead to reduced efficiency and

increased maintenance costs. To address these issues, the development and implementation of advanced battery management systems (BMSs) are both crucial. These systems are designed to control the charge and discharge cycles, thereby extending battery life and enhancing performance. Advanced BMSs can also incorporate real-time monitoring and predictive analytics to identify and mitigate potential issues. Furthermore, integrating these systems with IoT technologies can provide enhanced data collection and analysis, leading to more informed decision-making and improved operational efficiency. The adoption of such advanced management systems is essential for ensuring the long-term viability and reliability of battery storage solutions.

4. Ullah et al. [10] examined the challenges posed by the large-scale integration of EVs into the power grid. Sudden EV charging can strain transformers, leading to thermal overloads and reduced equipment lifespan. Additionally, the unpredictable load profiles of EVs further complicate demand forecasting and load balancing. To address these issues, bidirectional charging and blockchain-based control systems were proposed to enhance grid stability. Bidirectional charging enables both Vehicle-to-Grid (V2G or B2G) and Grid-to-Vehicle (G2V or G2B) technologies. However, V2G and G2V technologies face several challenges. These include the need for communication protocols, interoperability standards, and the management of battery degradation due to frequent charge–discharge cycles. To overcome these challenges, advanced algorithms and artificial intelligence (AI) methods are being developed to optimise V2G operations, ensuring efficient energy management. Furthermore, the integration of blockchain technology can enhance the security and overall performance of the transmission system by facilitating the real-time monitoring and control of energy flows. By addressing these challenges, the effective implementation of V2G and G2V technologies can significantly improve grid resilience and reliability.

1.2. Challenges of Renewable Energy Integration

Solar PV systems depend on weather conditions. This makes their power output inconsistent and unpredictable. These fluctuations can cause voltage and frequency instability in the grid, making it harder to balance electricity supply and demand. For example, a sudden drop in solar irradiance, such as when clouds pass, can reduce power output by up to 70% within minutes, putting stress on grid operations [11]. Inverter-based RESs have replaced traditional synchronous generators. This makes it more suitable for rapid frequency variation because solar inverters do not naturally support frequency stability like conventional generators do [12]. The decentralised nature of distributed energy resources (DERs), such as rooftop solar and battery storage, introduces further complexities. Bidirectional power flows from DERs can lead to voltage imbalances, reverse power flows, and transformer overloading into distribution networks. For example, uncoordinated EV charging during peak hours can increase demand by 20–30%, potentially causing voltage sags and equipment stress [13]. Addressing challenges such as ESSs, the integration of RESs, and power quality are essential for the effective implementation of modern grids as solutions. ESSs enhance grid capacity by storing surplus power generated from RESs and releasing it during periods of high demand or low availability. This capability stabilises the grid, reduces the impact of RES variability, and ensures a reliable power supply [14]. The integration of RESs into the grid is important for transitioning to a sustainable energy future. Advanced forecasting and distributed energy management systems can enhance the prediction and control of renewable energy source (RES) output, thereby balancing supply and demand in real-time. This integration not only enhances grid stability but also reduces reliance on fossil fuels, contributing to decarbonisation efforts [15]. Improvements in power quality, such as mitigating harmonic distortions and voltage fluctuations, are crucial for maintaining grid efficiency and reliability. Poor power quality can damage equipment and reduce efficiency [16]. Addressing these challenges is important because they are interconnected and affect the overall performance and sustainability of smart grids. By resolving issues related to battery storage, RES integration, and power quality, a more resilient, efficient, and sustainable energy system can be developed, supporting the global push toward decarbonisation and enhancing the reliability of power supply for consumers. This study proposes an IoT-based CBMS for rooftop solar-powered EV charging stations, which can use IoT technologies to create a smart and flexible platform for EV charging stations. Through IoT devices, different parts of the charging station communicate with the central monitoring system. The CBMS integrates IoT algorithms for real-time environmental monitoring and adaptive energy management, coupled with advanced DC-DC bidirectional converters for efficient power distribution.

To address grid instability, inefficiencies and the above challenges in conventional EVCSs, advanced system design must be integrated into key components effectively.

Table 1 shows function challenges and selection criteria for components that ensure efficient power conversion, storage and integration with grid. Figure 1 shows the block diagram of the proposed system. It utilises an advanced DC-to-DC converter, efficient control algorithms, real-time monitoring, and decision-making to improve grid efficiency and stability.

Table 1. Selection of key components in PV-based EV charging station design.

Component	Function	Related Challenges	Selection Criteria
Maximum power point tracking (MPPT) controller [17,18]	The MPPT controller is designed to extract the maximum possible power from PV panels by continuously adjusting the operating point based on varying environmental conditions. This is achieved by the smart control algorithms that track the maximum power point (MPP) of the PV array and ensure optimal energy harvest throughout the day.	• Fluctuations in solar irradiance, partial shading and temperature can lead to rapid changes in the MPP. • The controller must respond quickly to maintain efficiency.	• High tracking efficiency (>95%) is required to reduce power loss. • Fast dynamic response to changes in environmental conditions, such as solar irradiance, temperature, wind, and partial shading. • Compatibility with the PV array and converter topology.
DC-to-DC converter [19]	It converts the DC voltage from the PV output to either a step-up or step-down voltage based on the requirements of the battery or grid.	• Maintaining high efficiency. • Selection of appropriate topologies for specific renewable configurations.	• High efficiency (>95%), wide input voltage range, thermal stability, and compact design.
Bidirectional converter [20]	Enables power flow between battery and DC bus (charging/discharging).	• Maintaining bidirectional efficiency. • Complexity in control. • Selecting appropriate topologies for specific renewable configurations.	• Fast dynamic response. • Soft-switching topologies. • Advance control and protection features, including ZVS/ZCS and fast current sensing.
Smart grid integration [21,22]	Integrate a renewable system with the grid to manage power flow and stability.	• Voltage/frequency synchronisation, reactive power control, and power quality issues such as harmonic distortion. • To handle large RES generation, a smart control algorithm is required to control the variability and ESS.	• Integration of demand response and energy management advance algorithm. • It must be able to control and monitor distributed renewable energy resources (DERs) to maintain reliable and stable hybrid microgrid operation.
Battery sizing [23]	Determining the optimal battery capacity in smart and hybrid microgrids is essential for ensuring effective energy storage, load balancing, and peak-shaving performance.	• Requires accurate load forecasting and precise modelling of renewable-energy generation to avoid under- or over-sizing the storage system, which directly affects stability and cost.	• The CBMS should be able to monitor and control the battery's state-of-charge (SOC), improving reliability and bidirectional power flow control within advanced energy storage systems.

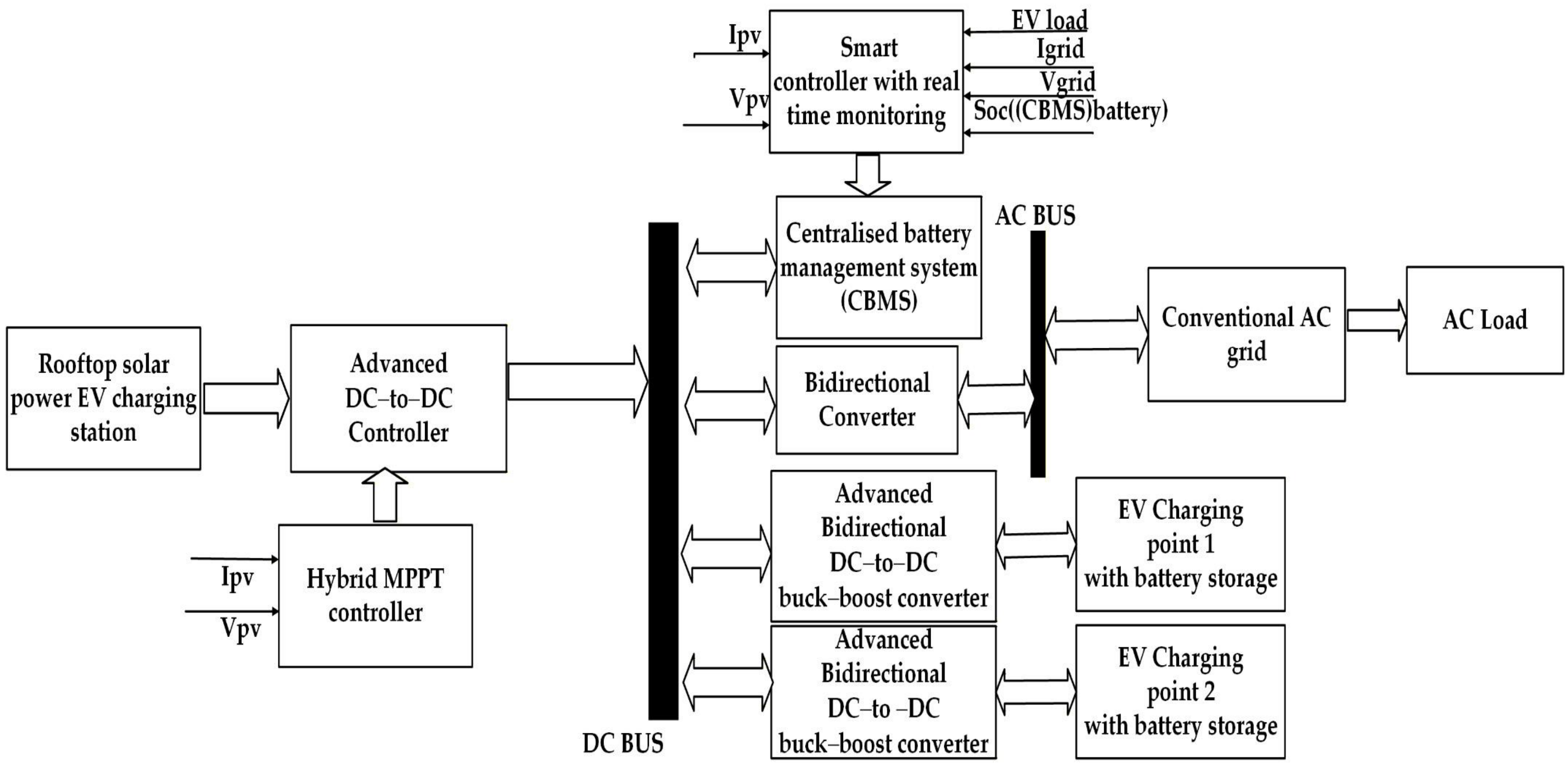

Figure 1. Block diagram of the proposed system.

2. Simulation-Based Analysis of Environmental Factors Affecting Solar Power Generation

Solar photovoltaic (PV) systems are an important part of RESs, but their performance depends heavily on the environment. Fluctuations in solar irradiance, temperature, humidity, dust accumulation, and cloud cover introduce significant instability in power output, which introduces variability in power output, battery charging efficiency, and grid stability. Accurate modelling and simulation of these environmental influences are essential for optimising system design, forecasting energy generation, and ensuring reliable grid integration [24]. This study demonstrates how solar generation systems respond to the above factors.

2.1. Solar Irradiance

Solar irradiance is the power per unit area received from the sun in the form of electromagnetic radiation, which affects the output of a solar cell. The amount of solar irradiance directly influences the amount of power generated by a solar cell. Higher irradiance means more photons are available to be converted into electrical energy, increasing the output power. Rainfall can reduce irradiance and leave behind water droplets or dirt streaks on panels, causing optical losses. Snow that falls on panels acts as a physical barrier to sunlight. Unless it melts or slides off, it can lead to complete generation loss.

The relation of power and solar irradiation is shown below [25]:

$$P = \eta \times E \times A_C \tag{1}$$

where

$$\eta = energy\ conversion\ efficiency,$$
$$E = Solar\ irradiance\ in\ \left(\frac{\mathrm{W}}{\mathrm{m}^2}\right),$$
$$Ac = surface\ area\ of\ the\ solar\ cell\ (\mathrm{m}^2).$$

Latitude affects both the duration of daylight and the angle at which the sun's rays strike the Earth. Regions at higher latitudes typically experience less sunlight, while those at lower latitudes experience more sunlight. Seasonal variations can also impact daily power generation due to changes in daylight and solar angles [25].

$$P_{daily} = \int_{sunset}^{sunrise} E(t) \cdot A_C \cdot \eta dt. \tag{2}$$

2.2. Ambient Temperature (T)

Ambient temperature is the temperature of the environment surrounding the solar panel. As the temperature increases, the voltage of a PV module decreases, reducing its efficiency. To describe the impact of temperature on the efficiency of the PV module, the temperature coefficient is defined. Wind speed affects the cooling of panels, modifying the cell temperature. The output voltage of a PV module at a specific temperature can be estimated as follows [26]:

$$V_{oc\ amb} = Temp.coff\ \times (T_{STC} - T_{amb}) \times V_{oc\ STC}, \tag{3}$$

where $V_{oc\ amb}$ denotes the open circuit voltage at ambient temperature T_{amb}, and $V_{oc\ STC}$ and T_{STC} are the open circuit voltage and temperature at standard test conditions (STCs), respectively. At 25 °C standard temperature and with a temperature coefficient ($Temp.coff$) of 0.33, the above equations can be written as follows [26]:

$$V_{oc\ amb} = 0.33 \times (25 - T_{amb}) + 36.30 \tag{4}$$

Relative humidity (RH) causes light scattering and transmission loss. Air quality issues, such as aerosols and dust, increase atmospheric attenuation and reduce irradiance. Soiling from dust on panels also reduces transmission. Combining the above factors, the comprehensive PV output equation considering all environmental effects is as follows [27]:

$$P_{actual} = P_{STC} \times \frac{E_{actual}}{E_{STC}} \times ([1 - Temp.coff\ (Tc - 25)] \times (1 - Ls - Sf - k{\cdot}RH), \quad (5)$$

where

Ls and Sf are soiling and shading losses, respectively,
$k{\cdot}RH$ is humidity-related loss.

Figures 2 and 3, derived from the NASA power database [28], illustrate the historical variations in solar irradiance and temperature in Auckland from 1 January 2020 to August 2025. Auckland was selected because the region's growing EV adoption and variable climate make it an ideal real-world test environment for evaluating rooftop solar EV charging behaviour. The figures present changes in the environmental factors affecting solar power generation in Auckland, New Zealand. Figure 4 shows changes in environmental factors such as solar irradiance (W/m^2), temperature (°C), wind speed (m/s), and humidity, which are measured as relative (%) in Auckland, New Zealand, on 7 January 2025 [28].

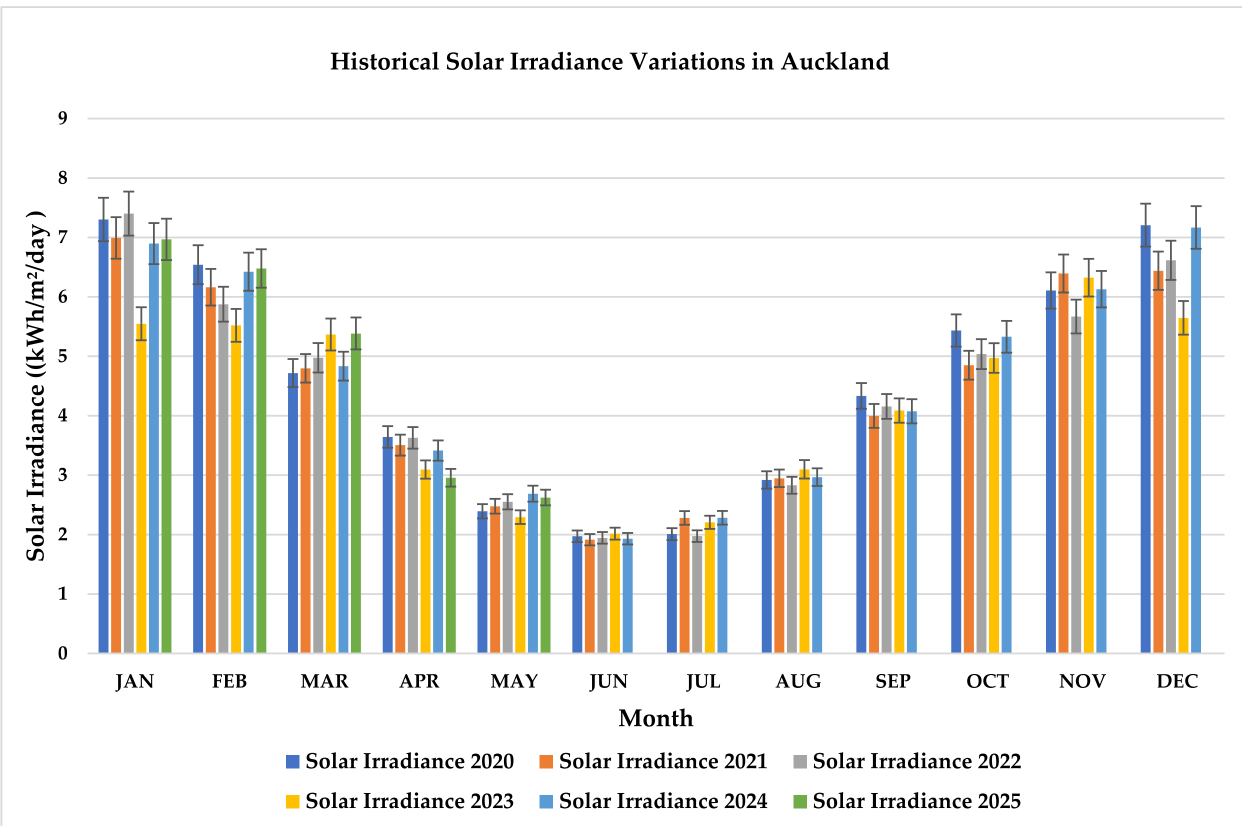

Figure 2. Historical solar irradiance variations in Auckland.

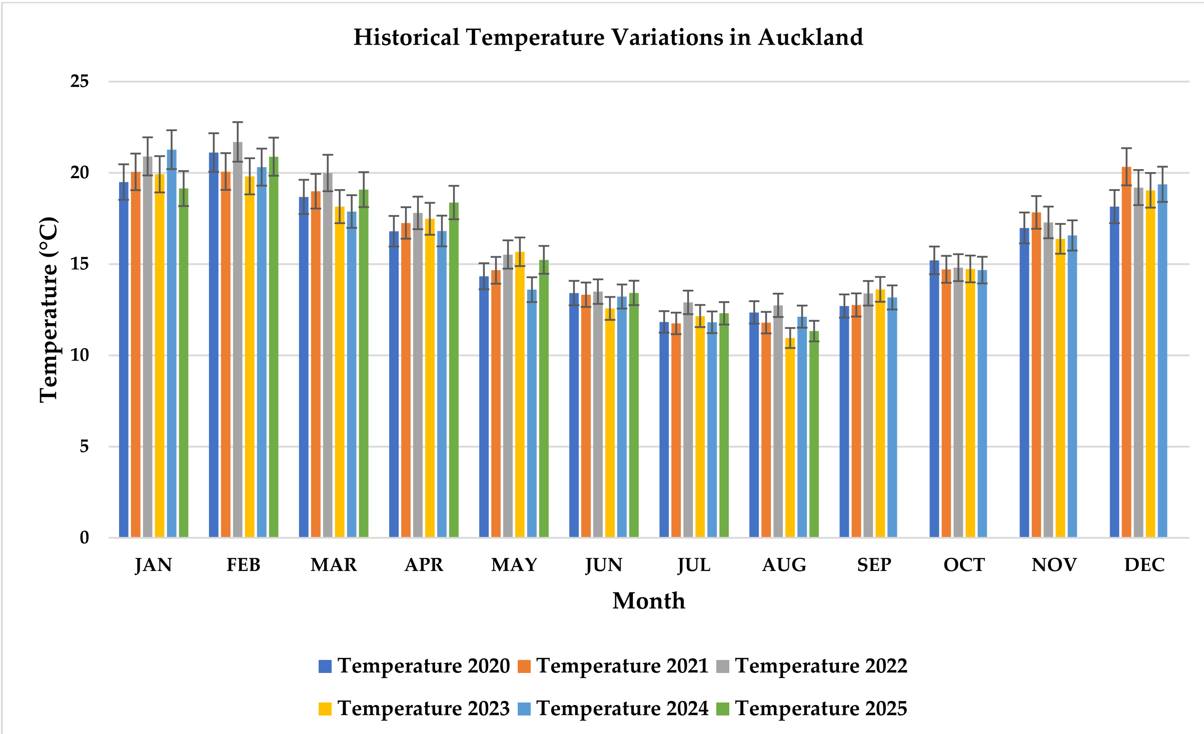

Figure 3. Historical temperature variations in Auckland.

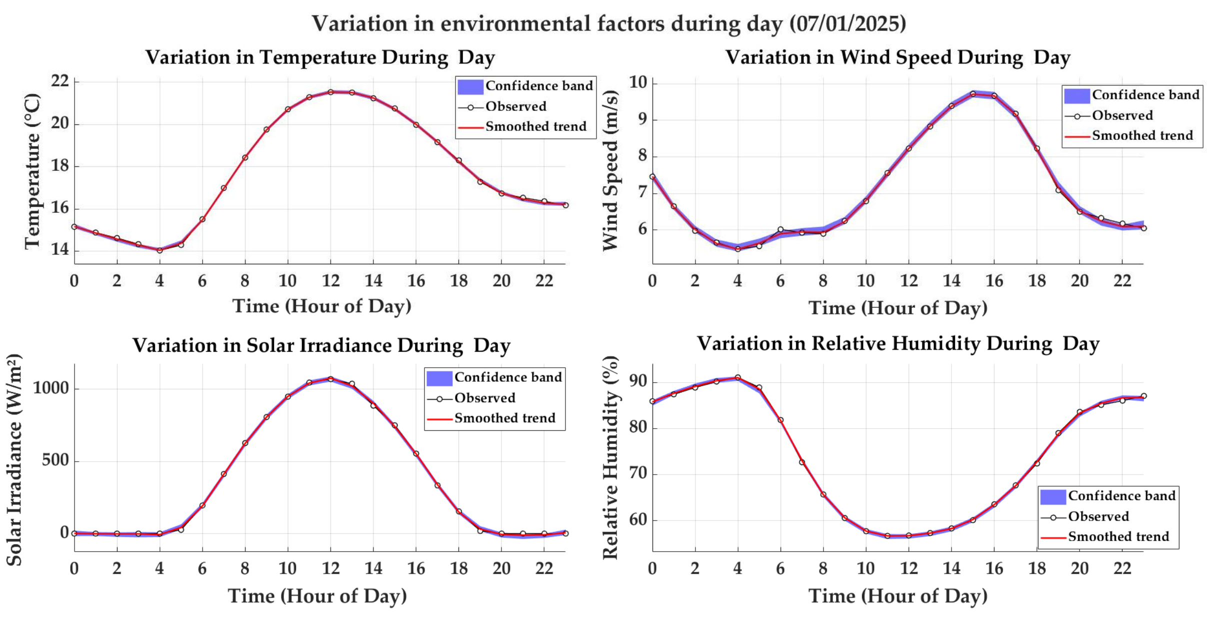

Figure 4. Variation in environmental factors during the day.

To study the variation, a MATLAB 2025b simscape electrical stimulation of 100 KWp (Kilowatt-peak) solar generation is developed. Figure 5 shows the simulation diagram of the system. Table 2 shows the simulation parameters used for solar generation.

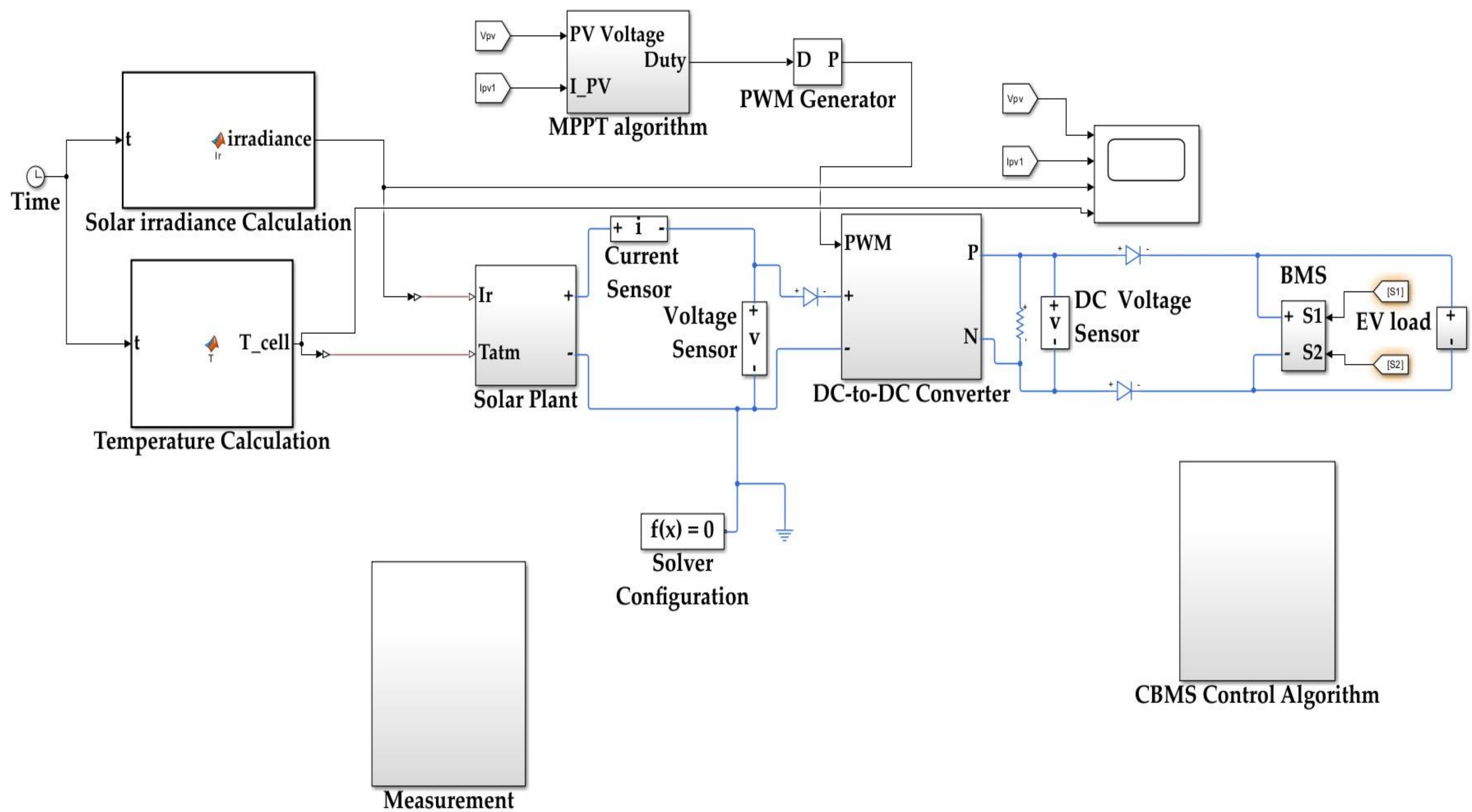

Figure 5. Simulation diagram of the solar power generation system.

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Table 2. Simulation parameters for solar generation and the EV charging station [29,30].

Parameter Category	Description	Values/Considerations
PV system parameters	Solar PV capacity	100 kW DC
	Area required	375–500 m^2
	Nominal power of PV	375 W
	Solar panel	Trina Solar Dumax_TSM_DEG14_72C_375 W
	No. of cells per module	72 cells
	Total nos. of PV panels	268
	Rated voltage (Vmp)	40.0 V
	Rated current (Imp)	9.31 A
	Open-circuit voltage—(Voc)	46.9 V
	Short-circuit current (Isc)	9.71 A
	Voc temperature coefficient	−0.3014%/°C
	Isc temperature coefficient	0.054604%/°C
	Light-generated current (IL)	9.6087 A
	Diode saturation current Io	3.5082×10^{-11} A
	Ideality factor of diode	0.96299
	Shunt resistance Rsh	1225.852 Ω
	Series resistance Rs	0.32701 Ω
Buck–boost converter	Switching frequency	20 kHz
	Inductor (L)	0.0009375 H
	Output capacitor (C)	0.00117 F
Centralised battery energy storage system	Capacity	290 Ah
	Battery nominal voltage	800 V
	Maximum charge and discharge power	232 KWh
	SOC operating range	0.20–1.0
Bidirectional buck–boost converter	Inductor (L)	0.0015 H
	Output capacitor (C)	0.00117 F
EV charging load parameters	Number of chargers	Two chargers (25 kW each)
	Charger type	Level 2 (7.2–22 kW)
	Energy consumption (per EV)	15–30 kWh per charge
	Daily EV energy demand	300 kWh/day (for 10 EVs at 30 kWh/charge)

Figure 6 presents the outcomes of a MATLAB simulation that examined the impact of environmental conditions, including solar irradiance and ambient temperature, on the performance of a rooftop solar PV system over a 24 h summer cycle in Auckland, New Zealand, on 7 January 2025. The voltage (A), current (B), irradiance (C), and temperature (D) profiles show realistic, non-symmetric, and noisy behaviours, reflecting the actual variability. Solar irradiance varies owing to cloud cover, and a reduction in irradiance caused by shading can result in a proportional decrease in power output. These dynamic variations have a direct impact on battery charging profiles, grid stability, and converter performance, highlighting the necessity of incorporating real-time environmental data into system modelling and control strategies. Solar irradiance is a critical factor in photovoltaic (PV) generation because it directly affects the generation of solar power. This study contributes to the development of control strategies, such as battery storage management, and the integration of other renewable sources, such as wind or hydropower, to ensure grid reliability.

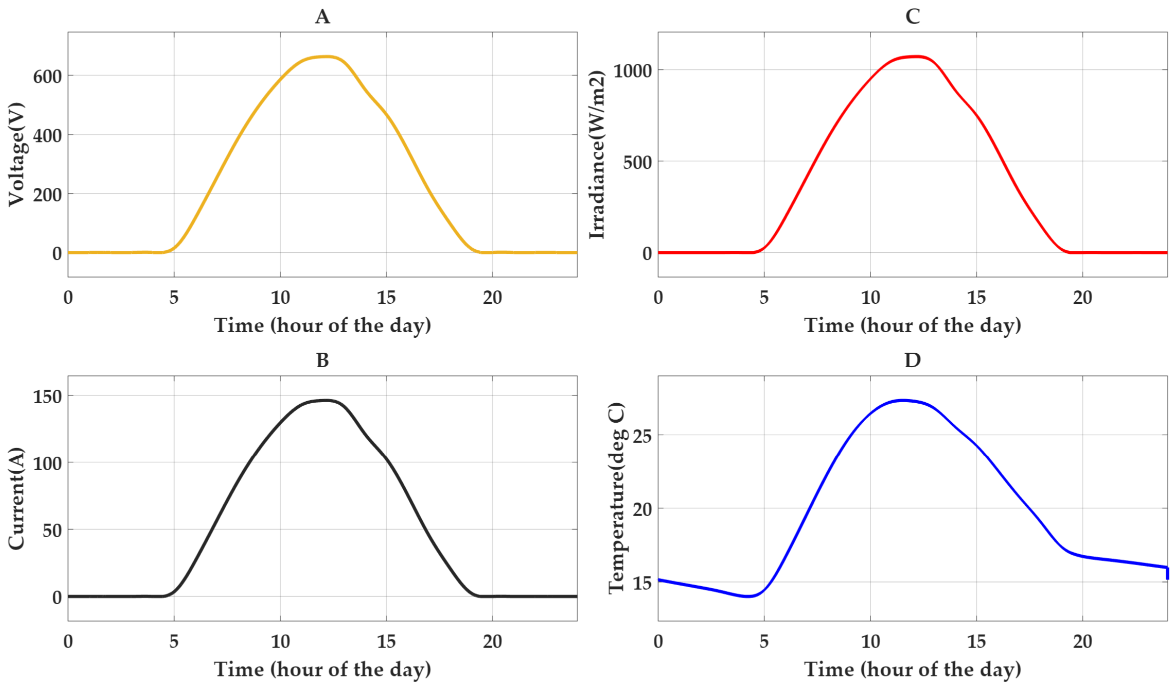

Figure 6. (**A**) Voltage variation, (**B**) current variation, (**C**) irradiance variation, and (**D**) temperature variation over time for solar generation.

Environmental variability leads to irregular charging profiles, which can cause three critical challenges: battery degradation, grid instability, and energy conversion losses. Irregular charging profiles caused by undercharging due to low irradiance from cloud cover or dust can lead to sulfation in lead-acid batteries and lithium plating in Li-ion cells, whereas overcharging from sudden irradiance spikes induces thermal stress and electrolyte breakdown, reducing the cycle life of the battery. Buck–boost converters dynamically adjust voltage and current to maintain optimal charging conditions, while precision constant voltage/constant current (CV/CC) phases prevent overcharging [31].

3. Role of DC-DC Converters

DC-DC converters are power electronic devices that are essential for converting a DC input voltage to a desired DC output voltage. They play a crucial role in various applications such as RESs, EVs, and consumer electronics. These converters utilise components such as inductors and capacitors to store and transfer power. Configurations such as buck, boost, and buck–boost topologies each offer unique advantages and applications [32]. The basic structure of a DC-DC converter typically includes inductors and capacitors for energy storage and filtering, along with switching elements that regulate the voltage conversion process. These converters are widely used in applications ranging from consumer electronics to industrial systems and EVs due to their compact size, control flexibility, cost and efficiency [33]. The operation of these converters involves switching a DC voltage source to produce a stable output voltage, with the average output controlled by adjusting the switching time. Advanced designs with control circuits and feedback controls are required to maintain output stability despite fluctuations in the input voltage [34]. Additionally, some converters use resonant components and transformers to enhance performance and efficiency, particularly in applications that require voltage isolation or transformation. Overall, DC-DC converters are integral to the efficient operation of a wide array of electronic devices and systems, facilitating the adaptation of power supply levels to meet specific operational requirements [35]. Furthermore, bidirectional converter designs support B2G functionality, enabling EVs to act as distributed power generation sources which can contribute to grid stability and demand response [36]. Despite these advancements, challenges such as maintaining efficiency at high duty cycles, electromagnetic interference (EMI) suppression, and ensuring interoperability with grid standards remain [37]. Addressing these issues through modern converter design and IoT-enabled energy management is essential for using the full potential of RES-integrated EV charging stations in future smart grid development [38].

DC-DC converters function as a bridge between RESs and storage units. Conventional unidirectional converters, such as buck, boost, and buck–boost topologies, are designed to transfer power unidirectionally (from the PV array to the battery/EV load). These converters are simple in design, cost-effective, and widely used in off-grid applications. However, they have some limitations, such as the inability to adapt to rapid environmental changes such as variations in irradiance or temperature. This can lead to poor maximum power point tracking (MPPT) and inefficient battery utilisation [39]. As the penetration of renewable energy and adoption of distributed battery storage continues to rise, advanced converter topologies and intelligent control algorithms that can overcome these limitations are required [40]. This study focuses on enhancing the adaptability, efficiency, and intelligence of unidirectional buck–boost converters through smart charging control, predictive energy management, and integration with a CBMS. With these upgrades, unidirectional converters can become more flexible and useful, even in advanced power systems.

Bidirectional Buck–Boost Converter with Smart Charging Control

The smart charging control bidirectional buck–boost converter provides flexibility to handle variations in solar input and enables both step-up and step-down operations as required by fluctuating irradiance and load demands. This dual-mode operation ensures that the converter can maintain stable and efficient energy transfer to the battery, regardless of whether the PV voltage is above or below the battery voltage [41].

Buck mode (PV voltage > battery voltage):

$$\frac{diL}{dt} = \frac{Vpv \cdot D - Vbat}{L}, \qquad \frac{dVbat}{dt} = \frac{iL \cdot D}{C} \tag{6}$$

Boost mode (PV voltage < battery voltage):

$$\frac{diL}{dt} = \frac{Vpv - Vbat \cdot (1-D)}{L}\ , \qquad \frac{dVbat}{dt} = \frac{iL \cdot (1-D)}{C} \tag{7}$$

where

Vpv = PV Voltage (input) (V);
$Vbat$ = Battery Voltage (V);
D = Duty Cycle;
L = Inductance (μH);
C = Capacitance (μF).

When integrated with smart charging control, the converter dynamically adjusts its duty cycle based on real-time battery state-of-charge (SoC), temperature, and load conditions. This enables precise regulation of charging current and voltage, which is critical for extending battery life and preventing degradation mechanisms such as lithium plating or thermal stress. The control strategy typically employs a PI controller with an SoC-adaptive voltage reference [42], depicted as follows:

$$D(t) = Kp \cdot (Vref(SoC) - Vbat) + Ki \int (Vref(SoC) - Vbat)\mathrm{dt} \quad (8)$$

where the reference voltage is:

$$Vref(SoC) = \frac{Vbat \cdot (1 + \alpha \cdot tanh(SoC - SoC(target)))}{\delta} \quad (9)$$

For SoC-based mode selection to prevent overcharging of battery, it only charges the battery when the following is true [42]:

$$SoC < SoC(target) - \Delta\ SoC \quad (10)$$

And stops charging when the following is true:

$$SoC > SoC(target) + \Delta\ SoC \quad (11)$$

where

- α and $\delta = 0.1$.
- Δ SoC = 0.05 for smooth operation.
- SoC(target) = 1.
- Kp = Proportional Gain = 0.5.
- Ki = Integral Gain = 10.

A buck–boost converter controlled by a smart charging algorithm for a BMS in a RES-integrated EV charging station offers buck/boost mode transitions as per requirements, faster response, and high efficiency. The higher efficiency of the smart control algorithm-based buck–boost converter shows how effectively the converter transfers power with minimal losses, inducing smart charging which increases the battery lifespan [43]. To evaluate the effectiveness of the proposed system, a comparative analysis was conducted between the buck–boost converter and conventional buck and boost converters. Table 3 shows the comparison of efficiency. The efficiency values for the conventional buck and boost converters were obtained through simulations using the same parameters listed in Table 2.

Table 3. Comparison of efficiency.

System	Efficiency of DC-to-DC Converter
Smart control system-based buck–boost converter	98.03%
Conventional system (buck converter)	97.16%
Conventional system (boost converter)	96%

Figure 7 presents the results of the MATLAB simulation of the smart battery charging control system. It is designed to optimise performance, safety, and longevity by adjusting the charging current and mode based on the battery's state-of-charge (SOC). This method is particularly useful for solar-integrated systems and electric vehicles, where efficient energy utilisation and battery health are important.

- Fast Charging Mode (SOC < 50%): In this mode, the battery is charged at a high charging rate when the state-of-charge (SOC) is below 50%. This is important during periods of high PV power generation when solar power production is at its peak. By increasing the charging rate during these times, we can efficiently use the available solar power and reduce dependency on grid power. Fast charging not only quickly charges the battery power but also ensures that the system can take full advantage of renewable energy sources. This mode is crucial for enhancing overall energy management.

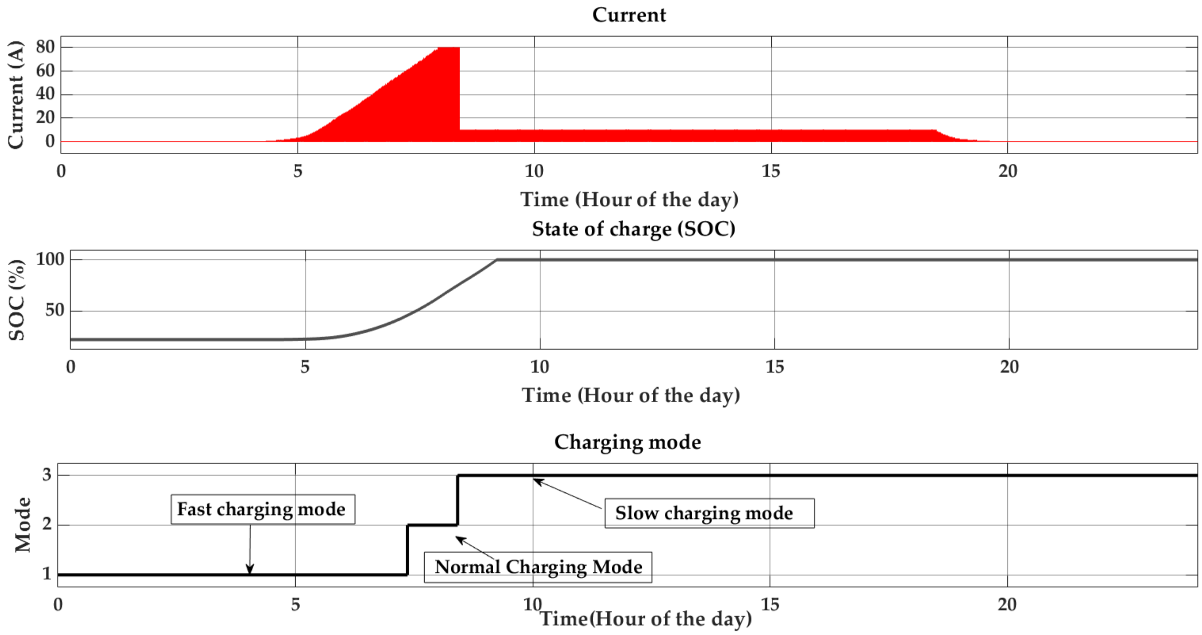

Figure 7. Battery charging control.

- Normal Charging Mode (50% ≤ SOC < 90%): When the state-of-charge (SOC) is between 50% and 90%, the charging rate is adjusted to a standard level. This adjustment is important for regulating the battery's internal temperature and reducing thermal stress on its components. High temperatures and excessive charging currents can lead to a faster degradation in the battery's lifespan. By maintaining operation within this SOC range, we can maintain the battery's health, ensuring it remains efficient and reliable over a long period. This not only improves the battery's operational life but also leads to cost savings.
- Slow Charging Mode ($SOC \geq 90\%$): In this mode, the charging process is slowed down when the SOC reaches 90% or higher. This approach is important for preventing overcharging batteries, which can lead to battery degradation and safety hazards, such as thermal stress and potential failure. By managing the charging rate in this range, we ensure that the battery is fully charged without compromising its integrity. This slow charging process is important for maintaining the battery's health, thereby extending its operational life and reducing the overall cost. A battery that lasts longer means fewer replacements and lower maintenance costs, contributing to significant long-term savings.

4. Smart CBMS Algorithm

Energy storage systems (ESSs) are becoming vital for modern power grids, especially as RESs becomes more popular. ESSs, such as batteries and supercapacitors, are important for stabilising the DC voltage bus and providing system stability, which is essential for controlling the variability in renewable energy generation [44]. Advanced control methods, such as G2B and B2G systems, further optimise the allocation of EV charging stations and RESs, ensuring that energy distribution aligns with the unpredictable nature of both RES generation and EV charging demands [45].

4.1. Key Roles of ESS in Modern Power Grids

- Grid Flexibility and Stability: ESSs help manage the variability and intermittency of renewables, such as wind and solar, ensuring stable and reliable grid operation. They provide fast frequency response, voltage regulation, and real-time balancing of supply and demand, which are essential for modern grids with high renewable penetration [46]. To maintain grid stability, ESSs must respond quickly to fluctuations in renewable generation. The SOC (state-of-charge) equation helps monitor available energy in real-time [47] and is express as follows:

$$SOC_t = SOC_{t0} + \frac{1}{C_{battery}} \int_{t0}^{t} P(t)dt, \tag{12}$$

where

$$SOC_{t0} = \text{Initial SOC},$$

$$C_{battery} = \text{Battery capacity (kWh)},$$

$$P(t) = \text{Power flow } (+\text{ve for charging}, -\text{ve for discharging}),$$

$$t = \text{Time}.$$

This equation helps monitor battery energy levels in real-time during both charging (G2V) and discharging (V2G) modes.

- Peak-Shaving and Load-Balancing: By storing excess energy during low demand and releasing it during peak periods, ESSs reduce the need for expensive grid expansion and help manage peak loads efficiently [36]. The power flow between the CBMS and the grid is calculated as follows [48]:

$$P_{CBMS}(t) = V_{bus}(t) \times I_{CBMS}(t), \tag{13}$$

where

$$P_{CBMS}(t) = \text{Instantaneous power}.$$

$$V_{bus}(t) = \text{DC bus voltage}.$$

$$I_{CBMS}(t) = \text{ Current from/to the CBMS}.$$

$$P_{CBMS}(t) > 0 : \text{ Charging mode}.$$

$$P_{CBMS}(t) < 0 : \text{ Discharging (B2G) mode}.$$

- Power Quality Improvement: ESSs contribute to voltage regulation, power factor correction, and reduction in grid congestion, thereby enhancing overall power quality and operational efficiency [49].
- Enhanced Grid Capacity: ESSs enhance grid capacity by providing backup power during peak demand and power outages. They also stabilise frequency after disturbances and improve overall system performance [50].
- Decentralisation and Microgrid Support: ESSs enable microgrids and decentralised power systems to operate both independently and in parallel with the main grid. ESSs also assist remote or rural regions to maintain continuity of power by supporting the local supply–demand balance.

The integration of RESs with ESSs in EV charging stations offers a promising solution for reducing dependency on the conventional power grid. By utilising solar power generation and storing it in batteries, EV charging stations can operate independently during periods of peak demand or grid outages [51]. This not only enhances the overall power transfer capability of the system but also reduces the stress on the grid. RES-based ESSs can be effective in various conditions, such as peak shaving, frequency regulation, and voltage support, contributing to improved grid stability and efficiency [52]. In this setup, solar PV is harvested and stored in a centralised ESS. The CBMS oversees the charge/discharge cycles and thermal conditions of the entire battery bank. When two EVs are connected to the station, the CBMS dynamically allocates power to each charging point based on real-time demand, battery state-of-charge (SoC), and grid availability. This centralised control ensures balanced energy distribution, prevents overloading, and increases the use of renewable energy, even during peak hours. The CBMS enables peak shaving by supplying stored energy during high-demand periods, reducing dependency on the grid. The CBMS serves as the central brain of the system, ensuring that both electric vehicle (EV) charging points and the grid operate efficiently and sustainably. IoT-based CBMSs can forecast energy demand, optimise charging schedules, and control variable renewable energy source (RES) inputs. The system's reliability is thus enhanced.

4.2. Control Algorithm

This algorithm enables real-time monitoring, load forecasting, and storage management, improving overall grid performance. To understand the control algorithm, it is divided into two distinct parts.

- Part A: Real-Time Monitoring and Forecasting.

Figure 8 illustrates real-time monitoring and load forecasting, which helps in understanding the variable generation of RESs. Real-time monitoring and load forecasting offer numerous advantages, particularly in the context of RESs. These features enhance predictive accuracy, providing precise forecasts of power generation and consumption patterns, which are important for integrating variable RESs into the grid. Improved grid stability is another significant benefit, as accurate load and generation forecasts help mitigate the fluctuations inherent in RESs, ensuring consistent power delivery. Additionally, these algorithms optimise resource allocation, reducing operational costs and enhancing the efficiency of energy distribution. The continuous monitoring capabilities enable proactive maintenance by detecting potential issues early, thereby reducing unexpected system failures and extending the longevity of the power infrastructure. Furthermore, these features make the algorithm scalable, flexible, and adaptable to various grid sizes and configurations, which is ideal for hybrid energy systems.

Load forecasting is an important part of the proposed CBMS algorithm. It enables proactive energy scheduling, efficient ESS utilisation, and improved coordination between RESs and EV charging demand. In a renewable-integrated EV charging system, there is high variability in generation as well as in EV charging patterns. Long short-term memory (LSTM) networks are more suitable for variable renewable generation and dynamic EV charging profiles. The forecasting process utilises real-time measurements combined with historical data, environmental variables, and behavioural indicators collected through sensors and communication devices. The predicted EV demand can be expressed as follows [53,54]:

$$\hat{P_{EV}}(t\ +\Delta \mathrm{t}) = f(P_{EV}(t)\,, SOC(t), E(t), T(t)) \tag{14}$$

where $P_{grid\ genration}$ and $P_{grid\ load}(t)$ represent generation and load power of the grid respectively. $P_{PV}(t)$ denotes PV generation and $P_{EV}(t)$ shows EV demand. $E(t)$ denotes solar irradiance, and $T(t)$ is ambient temperature.

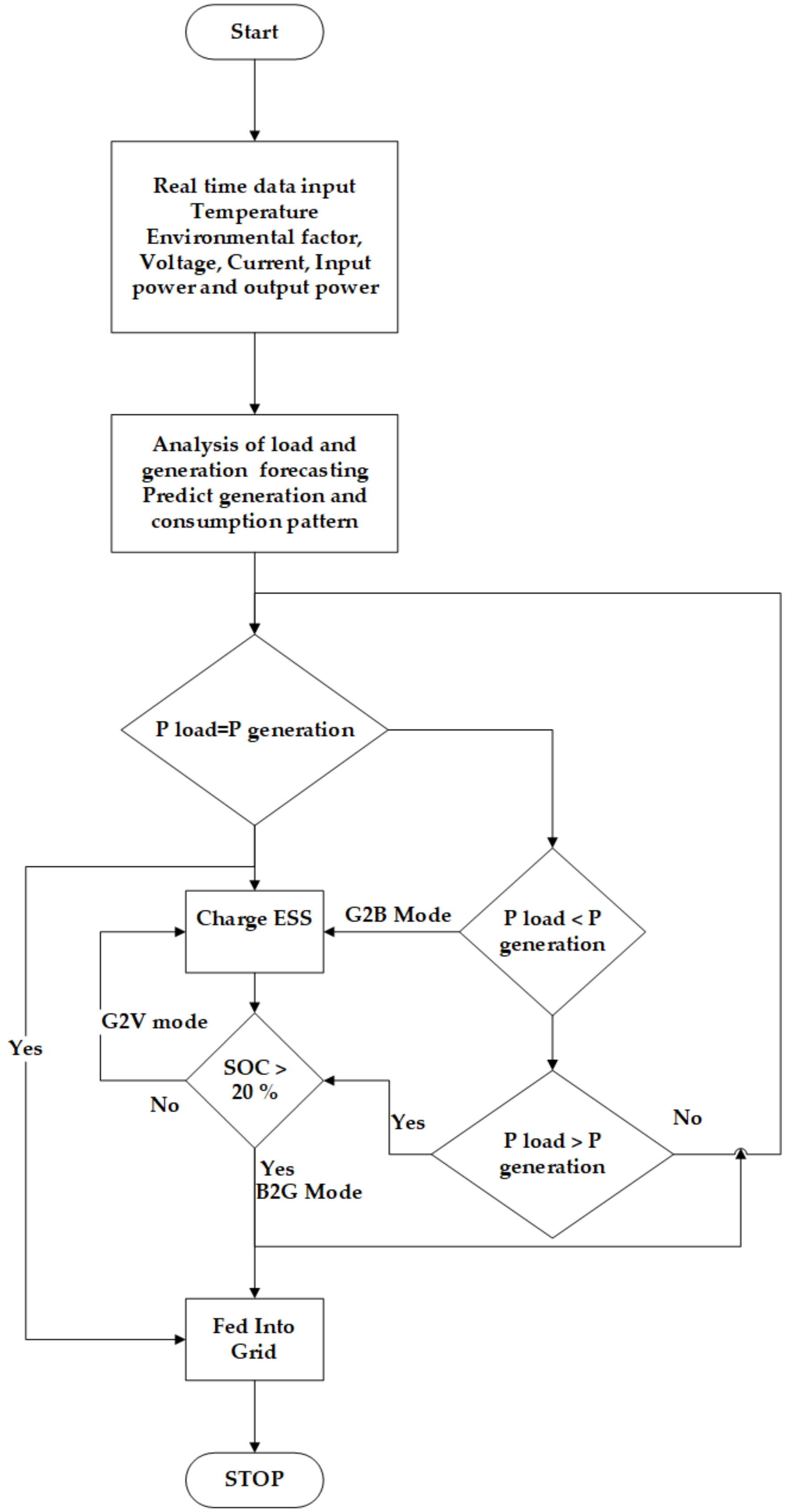

Figure 8. Flowchart of the IoT-based algorithm.

- Part B: Storage and Power Flow Management (B2G/G2B).

Figure 8 also illustrates the energy storage and management features of the algorithm, which are crucial for maintaining power supply and demand, controlling EV charging, and facilitating battery-to-grid (B2G) and grid-to-battery (G2B) interactions within the smart grid. This helps with the bidirectional flow of energy to enhance grid stability and flexibility, making it easier to integrate RESs and manage peak demand periods by optimising the use of ESSs. The supply and demand balance equation for the CBMS is expressed as follows [55]:

$$P_{PV}(t) + P_{CBMS}(t) + P_{grid\ genration}(t) = P_{EV}(t) + P_{grid\ load}(t) \quad (15)$$

ESS management and bidirectional energy flow control between the grid and battery happen through G2B and B2G operations. The SOC equation is denoted by the following [56]:

$$SOC(t+1) = SOC(t) + \frac{\eta_{\mathrm{ch}} \times \mathrm{P_{ch}}(\mathrm{t}) - \frac{\eta_{dis}}{\mathrm{P}_{dis}(\mathrm{t})}}{C_{battery}} \times \Delta t \quad (16)$$

where $\mathrm{P_{ch}}(\mathrm{t})$ and $\mathrm{P}_{dis}(\mathrm{t})$ denote charging and discharging power, respectively, and η_{ch} and η_{dis} represent efficiencies.

5. Results and Discussion

To evaluate the effectiveness of the system it is divided into three different modes. The system is modelled and analysed using MATLAB/Simulink 2025b to verify control performance, energy management efficiency, and bidirectional power flow capability under various operating scenarios.

- Normal Mode (Solar Priority): When photovoltaic (PV) generation is greater than or equal to electric vehicle (EV) charging demand, the system prioritises direct EV charging from PV [57].

$$P_{PV}(t) \geq P_{EV}(t) \quad (17)$$

The system prioritises direct EV charging using locally generated solar power to maximise renewable energy utilisation. The instantaneous power balance equation of the system can be expressed as follows [57]:

$$P_{PV}(t) = P_{EV}(t) + P_{CBMS}(t) \quad (18)$$

where the $P_{CBMS}(t)$ represents the charging power of the centralised battery management system (CBMS). If PV generation exceeds EV demand, the surplus power is utilised to charge the CBMS battery until the state-of-charge (SOC) reaches its maximum limit [57].

$$P_{CBMS}(t) = P_{surplus}(t) = P_{PV}(t) - P_{EV}(t) \quad (19)$$

Interaction with the grid is minimised to reduce dependency on conventional power sources. Power is exported to the grid if required. It maximises self-consumption (SC) and self-sufficiency (SS), which are important performance indicators for PV load-matching. This reduces grid stress by preventing unnecessary imports during solar hours, and enhances economic viability by using pollution-free solar energy instead of purchasing from the grid.

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- No Solar (Night or Cloudy): When PV output is approximately zero or less than Ev load, EV charging is provided by battery discharge. If the grid has surplus power, it charges the CBMS battery or the EV. This ensures service reliability for EV users, reduces dependency on the grid by prioritising stored solar power, and reduces the operational costs. The power balance equation of the system can be expressed as follows [58]:

$$If\ P_{PV}(t) = 0 \quad P_{CBMS}(t) = P_{EV}(t)\ or\ , \tag{20}$$

$$If\ P_{PV}(t) < P_{EV}(t) \quad P_{CBMS}P_{EV}(t) = P_{PV}(t) + P_{CBMS}(t) \tag{21}$$

Figure 9 shows the simulation results for the normal and no-solar modes during the unavailability of solar power. If the solar power is less than the required EV load, the battery discharges the power, as shown in the figure. During PV power, it is evident that the PV supplies the load and charges the battery using surplus power.

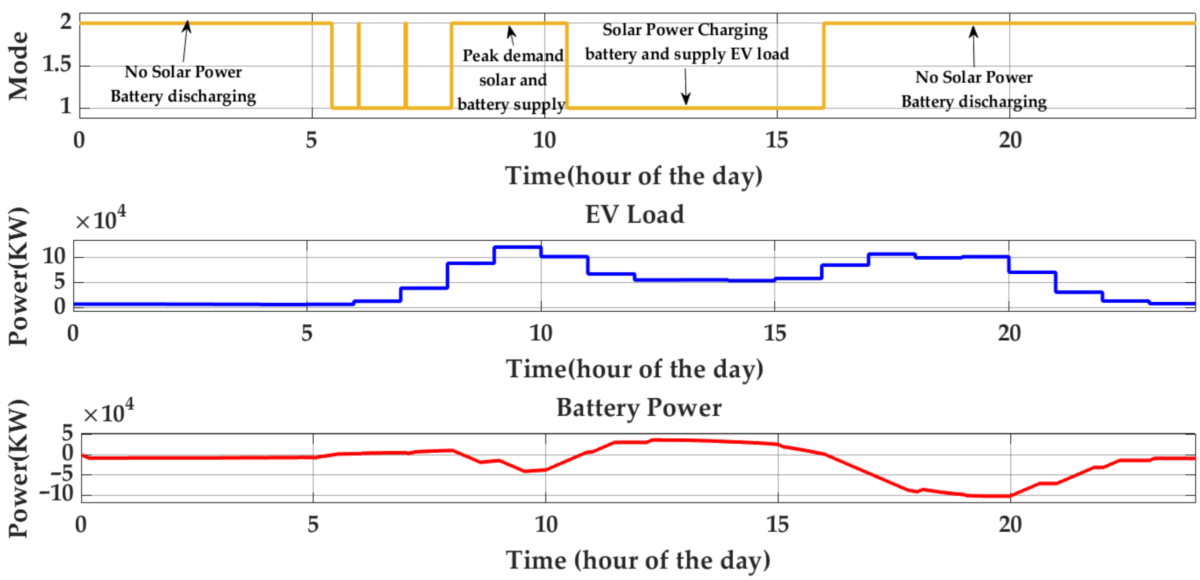

Figure 9. Power flow during No Solar and Normal modes.

- Grid Support (provides backup services to the grid): Activated during high demand or any unexpected disturbance occurs in the system. Charging electric vehicles (EVs) is temporarily stopped and stored energy is released back to the grid like the battery-to-grid (B2G) system within state-of-charge (SOC) and inverter limitations. EV charging can be delayed or rescheduled using smart charging algorithms to mitigate grid stress. It offers ancillary services to the grid, such as peak-shaving and voltage support. This lowers the risk of overloading transformers and feeders and improves the hosting capacity for distributed photovoltaic (PV) systems and electric vehicles (EVs). Figure 10 shows the total harmonic distribution (THD) and the FFT analysis of the grid current, revealing low harmonic distortion, which validates the effectiveness of the system in meeting grid power quality as per IEEE 519 standards [59].

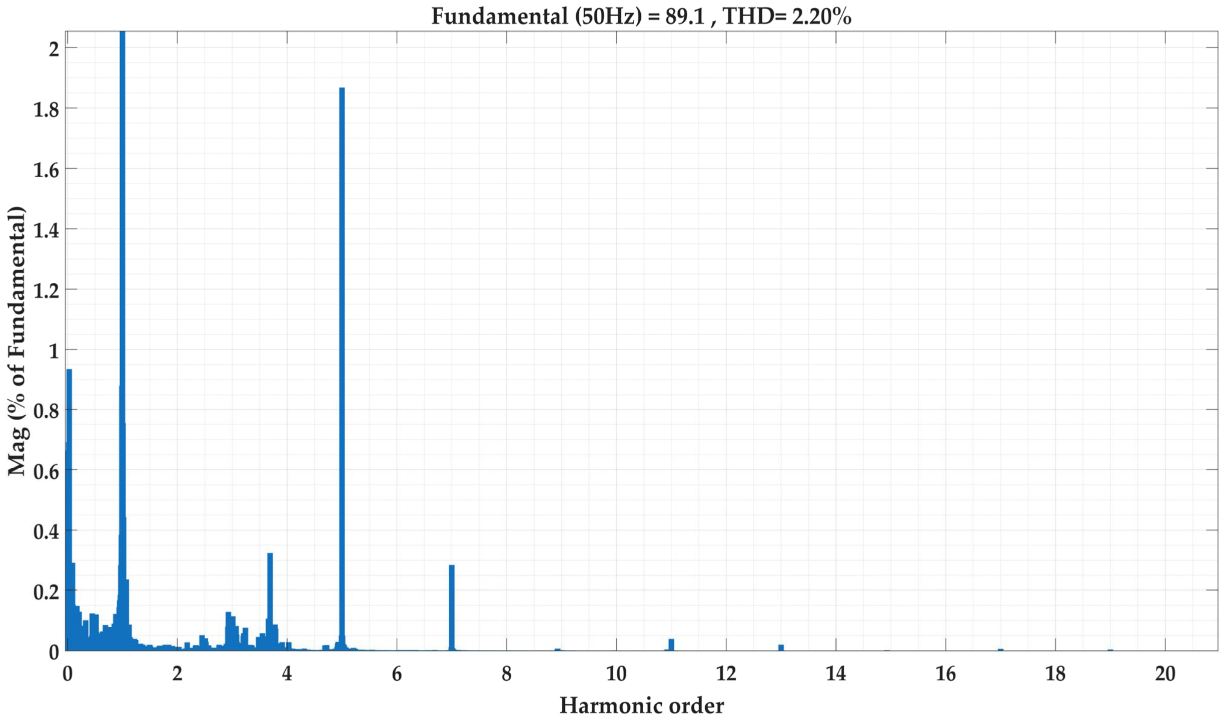

Figure 10. FFT analysis of the grid current during Grid Support mode.

6. Future Directions

Future research will focus on enhancing IoT-based centralised battery management systems (CBMSs) using artificial intelligence (AI) and machine learning (ML) algorithms. These techniques are expected to improve the real-time forecasting of solar irradiance, electric vehicle (EV) charging demand, and grid load profiles, which will help achieve more accurate energy scheduling, improved load balancing, and effective predictive maintenance strategies.

To validate our simulation results and address challenges within the grid, future work will integrate hardware-in-the-loop (HIL) testing which will be conducted under real-world conditions. This approach provides important insights into the operation of the CBMS and helps identify gaps between the simulated and actual performance. Further advancements are required to address the identified limitations of existing system components, such as traditional MPPT controllers, which remain limited by their focus on maximising instantaneous PV power without considering battery state-of-charge (SoC), degradation rates, thermal constraints, or grid support requirements. Bidirectional DC–DC converters also present opportunities for further improvements. Challenges such as switching losses, thermal stress, and high-frequency electromagnetic interference (EMI) must be mitigated to ensure a stable operation. Smart grid integration continues to pose challenges related to voltage instability, reverse power flow management, and harmonic distortion. Future studies will focus on designing more resilient grid support functions and improving interoperability standards to support distributed and decentralised energy systems. By addressing these interconnected challenges related to MPPT control, power conversion, grid integration, and energy storage, future work aims to support the development of efficient and advanced CBMS solutions which are capable of meeting the demands of future-generation smart grids.

7. Conclusions

This study investigates the impact of seasonal variations in solar irradiance on power generation, focusing on the integration of smart battery management systems. Specifically, it presents an innovative approach utilising DC-DC converters, including a bidirectional buck–boost converter with smart charging control topologies, to optimise power flow in rooftop solar-powered electric vehicle (EV) charging stations. To validate the proposed system, MATLAB simulations were conducted on a 100 kW solar power system. The results demonstrated that the smart-controlled buck–boost converter achieved an efficiency of 98.03%. Furthermore, the total harmonic distortion (THD) in Grid Support mode was measured at 2.28%, significantly lower than that observed in conventional boost or buck converter systems. These findings indicate that the proposed system not only enhances grid stability and power quality but also facilitates faster, safer, and more sustainable EV charging solutions.

In conclusion, the implementation of a smart CBMS effectively addresses the challenges posed by environmental variability. By optimising power management, the system enhances grid stability and reduces dependence on fossil fuels, thereby promoting sustainable energy solutions. The integration of smart charging technologies in EV infrastructure represents a significant advancement in the pursuit of efficient and environmentally friendly energy systems. This study underscores the potential of combining renewable energy sources with advanced control mechanisms to foster a more sustainable future for electric mobility and energy management.

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