Emmanuel Fialeseshie

Energy Optimization of Grid-Connected Hybrid PV-Battery Systems

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Author:	Emmanuel Fialeseshie
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ABSTRACT:

The growing integration of renewable energy sources into modern power systems has intensified the need for efficient energy storage and management solutions to address supply variability, ensure grid reliability, and minimize operational costs. This study is motivated by the technical and operational challenges associated with Battery Energy Storage Systems (BESS), particularly lithium-ion technologies, within hybrid photovoltaic (PV)-battery systems. The research aims to investigate these challenges, explore optimal control strategies, and develop practical recommendations to enhance the performance, lifespan, and economic viability of BESS. Specific objectives include formulating advanced control algorithms, analyzing system dynamics, and proposing best practices for BESS management in smart grid and microgrid environments.

A hybrid energy management system (EMS) was developed, combining Model Predictive Control (MPC) and Fuzzy Logic Control (FLC) to optimize power flow among PV generation, the battery, and the utility grid. Mathematical models capturing battery behavior, PV output, and grid interaction were designed under dynamic conditions such as variable tariffs and load profiles. The model was implemented and simulated using Python, with synthetic and real-world data over 24-hour periods to reflect residential, commercial, and industrial usage scenarios.

The results show that the proposed EMS significantly improves solar energy self-consumption, reduces reliance on the grid during peak tariff periods, and enhances battery cycling efficiency. FLC offered real-time responsiveness to rapid changes, while MPC provided anticipatory optimization over a forecast horizon. These findings highlight the potential of intelligent control strategies to support energy resilience and cost efficiency, offering scalable solutions for sustainable energy transitions in smart grid applications.

KEYWORDS: Battery Energy Storage Systems; Energy Management System; Model Predictive Control; energy systems

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Abbreviations

BESS	Battery Energy Storage System
PV	Photovoltaic
EMS	Energy Management System
MPC	Model Predictive Control
FLC	Fuzzy Logic Control
SOC	State of Charge
SOH	State of Health
AI	Artificial Intelligence
ML	Machine Learning
BMS	Battery Management System
CC-CV	Constant Current-Constant Voltage
EV	Electric Vehicle
TMS	Thermal Management System
UC	Ultracapacitor
DER	Distributed Energy Resource
EKF	Extended Kalman Filter
DOD	Depth of Discharge

1 Introduction

Battery energy storage has gained much increasing attention in recent years due to the increasing integration of renewable energy sources and efficient energy management (Li et al., 2018; Sintianingrum, 2020; Yi et al., 2022). Energy storage systems, especially batteries, have proven essential in smoothly running renewable energy through regulation of its intermittency and reliable power supply (Gür, 2018). Battery system deployment has widened and now calls for effective management and optimal control techniques to extend energy storage's performance, durability and economic benefits.

Recent advancements in battery technology, particularly lithium-ion batteries, have significantly improved the suitability and cost-effectiveness of energy storage systems (Zeng et al., 2019). However, the inherent complexity of battery systems presents ongoing challenges. To address these, researchers have developed advanced control strategies, optimization algorithms, and intelligent energy management systems (EMS) specifically designed to enhance battery performance and reliability (Lipu et al., 2021; PS Jayalakshmi & Kedlaya, 2020; Xiong et al., 2018).

One crucial element concerning battery energy storage management is the correct estimation and prediction of battery state-of-charge (SOC) and state-of-health (SOH) (Xiang et al., 2023). Different strategies, such as model-based approaches and data-driven methods, have been suggested to ensure the accuracy and robustness of SOC and SOH (Wan et al., 2022; Wei et al., 2021). Huang et al. (2021) are the innovators of an indirect health indicator characterised by constant current charging profiles, whereas Zhang et al. (2018) and Sun et al. (2015) both utilise hybrid approaches that Zhang et al. (2018) specialise in a hybrid of genetic algorithm and particle swarm optimisation, and Sun et al. (2015).

In addition, integrating battery storage systems into smart grid and microgrids brings new energy optimisation and management prospects. Jayawardana et al. (2018) and Adhikari et al. (2020) considered the economic benefits arising from this integration, in particular highlighting the possibility of reducing costs (Jayawardana et al., 2019). Ibrahim and Ghandour contributed to the optimisation of microgrids through a solar-diesel-battery hybrid system, and Ningzhou introduced an optimisation and dispatching model for microgrids with Na/S battery storage (Ibrahim & Ghandour, 2018; Ningzhou, 2011). To a large extent, the research mentioned above shows how battery storage systems influence the energy management and optimisation of smart grid and microgrid systems.

Also, incorporating artificial intelligent (AI) and machine learning (ML) techniques into battery energy storage management and optimisation is inarguably a significant innovation. AI-based methods like deep learning and neural networks have been proven to be quite effective in predicting the performance of batteries, optimising energy dispatch, and controlling predicted repair (Chemali et al., 2018). AI-based battery management systems (BMSs) improved performance and reduced the maintenance cost of energy storage systems with Li-ion batteries (Suciu et al., 2021). Additionally, Cordeiro-Costas et al. (2021) illustrate the application of ML methods in optimising the electrical demand of a building with storage management and, therefore, lower electricity expenses.

1.1 Research motivation

The growing penetration of renewables in electric power systems has made it evident that energy storage technologies are crucial for grid stability, reliability, and flexibility. Among the varieties of storage options, Battery Energy Storage Systems (BESS) have been in the limelight for their multifaceted, scalable and decreasing costs. Nevertheless, the challenge of successfully integrating and utilising BESS in power systems remains complex and requires highly advanced management strategies and operation algorithms. This study aims to explore the technical and operational challenges that hinder the integration of BESS and realise their full potential as a support for transitioning to sustainable energy systems. Through the in-depth research of battery behaviour, formulation of novel algorithms for effective control, and innovation of best practices in BESS management, this study aims to close the gap between theoretical advancements and practical realisations.

Another reason for performing this study is the prospective socio-economic and environmental benefits of having BESS optimised for power systems. Competent BESS management would contribute to reducing energy costs, enhancing grid resilience, and increasing the share of renewable energy in the energy market, thus facilitating all the processes associated with decarbonising the entire energy sector. Through policy recommendations and guidelines, this research provides the framework for efficient implementation of BESS in power systems, making it easy for power systems to adopt and operate effectively.

1.3 Problem statement

The spike in renewable energy sources has stimulated the priority of energy storage systems, particularly battery BESS, to secure a reliable and stable power supply (Gür, 2018). Nevertheless, with BESS incorporation into existing power systems, several technical and operational challenges need to be taken care of for them to be successfully deployed and operated at the highest capacity.

A significant obstacle is the complexity of battery systems, including electrochemical processes and degradation occurrences (Xiong et al., 2018). Precise battery state-of-charge (SOC) and state-of-health (SOH) calculation is critical in battery operation and upkeep management decision-making. However, current techniques do not have the required accuracy, robustness, and flexibility to varying conditions (Wei et al., 2021).

Another challenge is associated with the connection of BESS to smart grids and microgrids, which interact with other distributed resources and occasionally face dynamically changing energy prices and load patterns (Li et al., 2020). The subsequent issue is efficient distribution network sizing and siting, where modelling is required for optimal results (Zidar et al., 2016). Furthermore, as the penetration of Distributed Energy Resources (DERs) like BESS in microgrids increases, concerns like voltage transients, frequency deviation, power quality deterioration and, consequently, grid reliability and power stability (Ganesan et al., 2020).

Also, there is a knowledge gap in the literature regarding studies on the best practices for optimising battery energy storage management and operation in various power system contexts. Existing studies often focus on specific aspects of BESS integration, such as technical feasibility or economic viability (Hameed et al., 2021; Ray et al., 2015; Huu, 2021; Delfanti et al., 2019), without providing holistic recommendations for system operators and policymakers.

This study seeks to solve the problems raised and redress the identified gap by investigating the technical and operational challenges of integrating BESS into power systems. It will determine operational strategies and control algorithms to get the most out of battery energy storage assets in terms of value and performance. In addition, the study aims to provide policy recommendations and best practices in battery energy storage management and operation, taking into account the multiple stakeholders of the energy sector.

By achieving these objectives, this study contributes to advancing knowledge and practical solutions for effectively integrating and optimising BESS in power systems. The findings will support system operators, policymakers, and researchers in making informed decisions and developing strategies to harness the full potential of battery energy storage in the transition towards sustainable energy systems.

1.4 Objective

The objectives of this thesis are to

- Investigate the technical and operational challenges of integrating battery energy storage into existing power systems.

- Examine operational strategies and control algorithms for maximising the value and performance of battery energy storage assets.
- Develop policy recommendations and best practices for optimising battery energy storage management and operation.

2 Literature review

Battery Energy Storage Systems (BESS) have emerged as a crucial technology in modern power systems, playing a pivotal role in addressing the challenges associated with the integration of renewable energy sources and the increasing demand for grid flexibility. BESS offer a versatile solution for storing electrical energy and releasing it when needed, thereby enhancing grid stability, reliability, and efficiency (Gür, 2018).

The growing adoption of intermittent renewable energy sources, such as solar and wind power, has necessitated the deployment of energy storage technologies to balance supply and demand. BESS can effectively mitigate the variability of renewable generation by storing excess energy during periods of high production and discharging it during low production or high demand periods (Denholm et al., 2020). This capability not only improves the integration of renewables but also enhances grid resilience and reduces the need for fossil fuel-based plants.

BESS encompass various battery technologies, with lithium-ion batteries currently dominating the market due to their high energy density, long cycle life, and decreasing costs (Ziegler et al., 2019). However, other technologies such as flow batteries, sodium-sulfur batteries, and advanced lead-acid batteries are also being explored for specific applications and use cases (Koohi-Fayegh & Rosen, 2020).

The applications of BESS in power systems are diverse and include frequency regulation and grid stabilization, peak shaving and load levelling, renewable energy firming and smoothing, energy arbitrage and market participation, backup power and black start capabilities and transmission and distribution deferral.

Recent advancements in battery technology, power electronics, and control systems have significantly improved the performance and cost-effectiveness of BESS. For instance, the development of advanced battery management systems (BMS) has enhanced the safety, reliability, and longevity of battery installations (Xiong et al., 2018).

The integration of BESS into power systems presents both opportunities and challenges. While BESS offer numerous benefits, their optimal deployment requires careful consideration of factors such as sizing, placement, and operational strategies (Li et al., 2020). Moreover, regulatory frameworks and market structures need to evolve to fully capture the value of BESS and incentivize their deployment (Bhatnagar et al., 2013).

As the power sector continues to transition towards a more sustainable and decentralized model, BESS are expected to play an increasingly important role. Future developments in battery technology, such as solid-state batteries and novel chemistries, promise to further enhance the capabilities and cost-effectiveness of BESS (Masias et al., 2021)..

2.1 Lithium-Ion batteries

Lithium-ion batteries (LIBs) have revolutionized the energy storage landscape due to their high energy density, long cycle life, and declining costs. These rechargeable batteries consist of a lithium-containing cathode, a graphite anode, an electrolyte, and a separator (Xu et al., 2020). During discharge, lithium ions move from the anode to the cathode through the electrolyte, while electrons flow through an external circuit, generating electricity. This process reverses during charging (Liu et al., 2019). The structure of a lithium-ion (Li-ion) battery is shown in Figure 1.

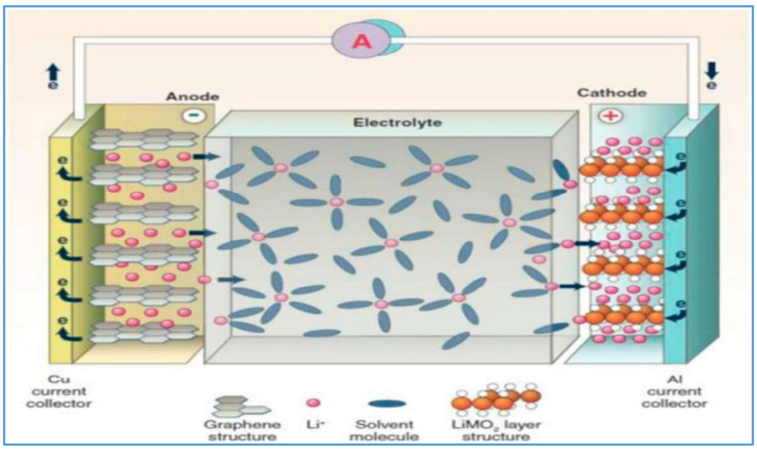

Figure 1 **Figure 1.** Structure of a lithium-ion (Li-ion) battery (Source: Yang & Hou, 2012).

LIBs come in various chemistries, including lithium cobalt oxide (LCO), lithium iron phosphate (LFP), and nickel-manganese-cobalt (NMC), each offering different performance characteristics and trade-offs (Zubi et al., 2018). Recent advancements have focused on improving energy density, safety, and charging speeds. For instance, silicon-based anodes and solid-state electrolytes are being developed to enhance battery performance and safety (Choi & Aurbach, 2016).

The widespread adoption of LIBs in electric vehicles, portable electronics, and grid-scale energy storage has driven significant research and development efforts. Their ability to deliver high power output and their relatively low self-discharge rates make them suitable for these diverse applications (Goodenough & Park, 2013). As the demand for renewable energy and electric vehicles (EVs) grows, the Li-ion battery market is expected to expand significantly, driven by continuous technological advancements and economies of scale (BloombergNEF, 2023).

2.2 Solar power systems

Solar power systems harness energy from the sun and convert it into electricity, offering a clean and renewable energy source. Key components of a solar power system include monocrystalline or polycrystalline silicon photovoltaic (PV) panels, which offer high efficiency and durability (Green et al., 2021). Solar inverters, essential for converting generated electricity to a usable form, have evolved to include smart functionalities for better integration with grid systems and enhanced energy management (Zhao et al., 2018).

PV panels are the core of solar power systems, utilizing semiconductor materials (usually silicon) to convert sunlight directly into electricity through the PV effect. Recent advancements in PV technology have led to increased efficiency and reduced costs, making solar power increasingly competitive with traditional energy sources (Green et al., 2021).

Inverters play a crucial role in solar power systems by converting the direct current (DC) produced by PV panels into alternating current (AC) for use in homes or feed-in to the grid. Modern inverters often include smart features for system monitoring and optimization (Eltawil & Zhao, 2010).

Solar power systems can be categorized as grid-connected, standalone, or hybrid, each serving different purposes and locations. Grid-connected systems are prevalent in urban areas, allowing bidirectional energy flow with the grid (Muntwyler, 2020). Standalone systems, often used in remote locations, operate independently and may include battery storage for energy accumulation (Karthikeyan et al., 2017). Hybrid systems combine multiple energy sources, enhancing reliability and flexibility (Meinhardt & Cramer, 2000).

Recent trends in solar power systems include the integration of energy storage, development of bifacial panels, and use of tracking systems to maximize energy capture. Energy storage solutions, such as batteries and thermal storage, address intermittency issues and enable grid integration (Hasan et al., 2023; Hill et al., 2012).

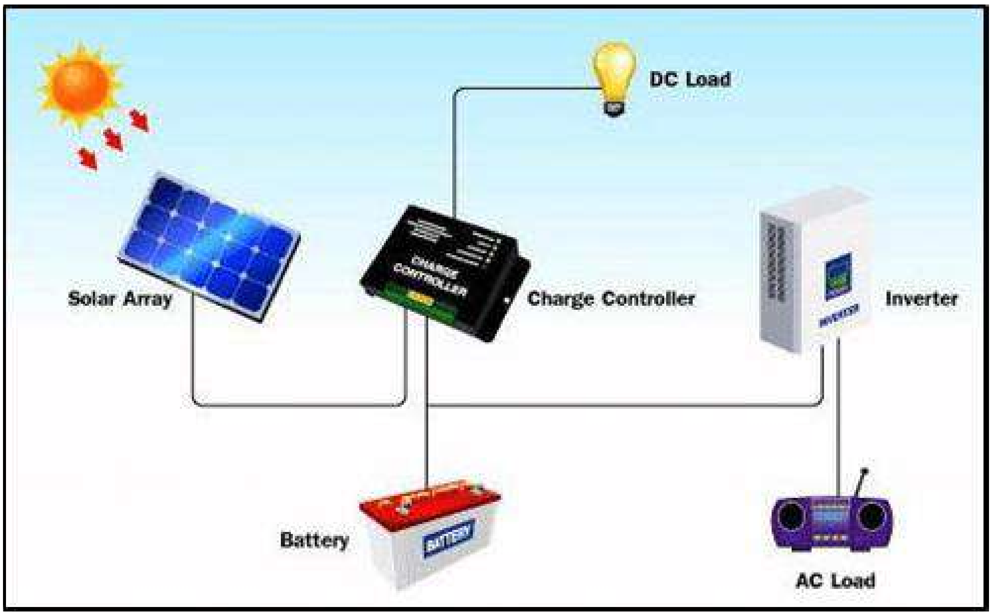

Figure 2**Figure 2.** Solar power systems (Source: www.leonics.com)

2.3 Technical and operational challenges of integrating lithium-ion (Li-ion) batteries into solar panels

2.3.1 Technical challenges

System design and sizing: Determining the optimal configuration of solar panels and battery capacity is a complex technical challenge. Akram et al. (2020) highlight the importance of matching battery capacity with solar panel output and load requirements to ensure efficient operation and economic viability. Undersizing can lead to insufficient energy storage, while oversizing increases costs and may result in underutilization. Parizad & Hatziadoniu (2019) propose a multi-objective optimization approach for sizing hybrid solar-battery systems, considering factors such as reliability, cost, and environmental impact.

Power electronics and control systems: Advanced power electronics and control systems are essential for managing energy flow between solar panels, batteries, and the grid or load. Hannan et al. (2018) emphasize the crucial role of inverters in this integration, converting DC power from solar panels and batteries to AC power for use or grid feed-in. Some studies propose an advanced inverter control strategy for grid-connected solar-battery systems, improving power quality and system stability under varying conditions (Alam et al., 2015; Lyu et al., 2017; Yang et al., 2014). These strategies include flexible power control for ancillary services (Yang et al., 2014), multi-mode VAr control for voltage support (Alam et al., 2015), and frequency support using DC-link capacitors and deloading (Lyu et al., 2017).

Battery Management Systems (BMS): Effective battery management is critical for safe and efficient operation. The BMS must monitor and control parameters such as state of charge (SOC), state of health (SOH), temperature, and voltage. Zhang et al. (2020) review recent advancements in BMS for Li-ion batteries, highlighting the importance of accurate SOC estimation and thermal management, and noting the increasing application of machine learning (ML) techniques to improve BMS performance.

Thermal management: Li-ion batteries are sensitive to temperature variations, which can significantly affect their performance, lifespan, and safety. Liu et al. (2019) discuss the challenges of maintaining optimal battery temperature in solar applications, where batteries may be exposed to a wide range of environmental conditions. Arora et al. (2018) investigate various thermal management strategies, finding that passive cooling methods can be effective in many solar applications, but active cooling may be necessary for high-power or extreme environment scenarios.

Safety and reliability: Ensuring the safety and reliability of Li-ion batteries in solar applications is a critical technical challenge. Kong et al. (2018) discuss potential risks including thermal runaway, short circuits, and electrical fires. Addressing these concerns requires a combination of advanced battery chemistries, robust BMS, and proper system design. Wang et al. (2020) explore the use of solid-state electrolytes as a means to improve safety and reliability, though challenges in manufacturing scalability and long-term performance remain.

2.3.2 Operational challenges

Degradation and aging: Li-ion batteries experience capacity fade and performance degradation over time, impacting the long-term reliability and efficiency of solar-battery systems. Recent studies examined the impact of various operating conditions on Li-ion battery aging in solar applications, finding that factors such as depth of discharge, charge/discharge rates, and temperature cycling significantly influence degradation rates (Preger et al., 2020; Collath et al., 2022). This emphasizes the need for optimized operational strategies to extend battery life.

Grid integration and energy management: Integrating solar-battery systems with the existing power grid presents operational challenges related to power quality, grid stability, and energy management. Li et al. (2020) discuss the need for advanced control strategies to optimize the interaction between solar-battery systems and the grid, considering factors such as energy prices, grid demand, and renewable energy generation forecasts. Karami et al. (2020) proposed a novel energy management system utilizing ML techniques to optimize energy dispatch and maximize economic benefits.

Environmental and resource considerations: The production and disposal of Li-ion batteries have significant environmental implications. Harper et al. (2019) review the current state of Li-ion battery recycling and propose strategies for improving resource recovery and reducing environmental impact. They emphasize the need for design-for-recycling approaches and the development of more efficient recycling technologies to create a circular economy for battery materials.

Economic viability and cost optimization: While costs have decreased, the economic viability of integrated systems remains a challenge in many contexts. Ziegler et al. (2019) analyze the economics of solar-battery systems, identifying key drivers of economic viability. Comello and Reichelstein (2019) propose strategies for cost optimization, finding that factors such as local electricity prices, solar resources, and regulatory frameworks significantly influence the economic attractiveness of these systems.

Standardization and interoperability: The lack of standardization in solar-battery system components and interfaces can lead to operational challenges and increased costs. Barbosa et al. (2018) discuss the importance of developing industry-wide standards for system design, communication protocols, and performance metrics to improve interoperability and facilitate widespread adoption.

2.4 Operational strategies for maximizing the value and performance of lithium-ion batteries

Operational strategies for maximizing the value and performance of lithium-ion batteries in solar power systems are crucial for ensuring optimal system efficiency, longevity, and economic benefits. These strategies encompass various aspects of battery management and system operation.

Constant Current-Constant Voltage (CC-CV): The CC-CV charging method is widely used for lithium-ion batteries, offering efficient charging and protection against overcharging

(De & Dey, 2021; Falih et al., 2021). This method involves maintaining a constant current until specific conditions are met, followed by a constant voltage phase (Suryoatmojo, 2021).

Pulse charging: Pulse charging, which involves applying intermittent charging pulses with rest periods, has shown promising results in enhancing battery lifespan and reducing heat generation. Multiple studies have demonstrated that pulse charging can improve battery performance compared to conventional CC-CV charging (Amanor-Boadu et al., 2018; Amanor-Boadu & Guiseppi-Elie, 2020). This technique can reduce charge time, increase charge and energy efficiencies, and extend battery cycle life (Amanor-Boadu & Guiseppi-Elie, 2020).

Fast charging: Employing high currents for shorter periods, carefully managed to avoid overheating and degradation. High currents can lead to capacity loss, power fading, and thermal runaway (Abd El Halim et al., 2023). Optimal charging strategies aim to minimize charging time while managing battery health and safety (Salyer et al., 2021).

2.4.2 Temperature management

Active cooling/heating: Active cooling and heating systems are crucial for maintaining optimal battery temperature in electric vehicles (EVs). Lithium-ion batteries perform best between 15-35°C, with temperatures outside this range leading to performance degradation and safety risks (Hwang et al., 2024).

Thermal Management Systems (TMS): Integrated systems that monitor and regulate battery temperature through passive and active methods (Wankhede et al., 2022).

2.5 State of Charge (SOC) and State of Health (SOH) Monitoring

SOC Estimation: Implementing algorithms to accurately estimate the battery’s charge level, ensuring safe and efficient use (Kaushik et al., 2021).

SOH Monitoring: Tracking battery health metrics to predict and prevent potential failures (Bokstaller et al., 2024).

2.6 Load Management

Peak Shaving: Reducing the load during peak demand times to minimize stress on the battery. Peak shaving using battery energy storage systems (BESS) is an effective strategy to reduce local and global peak loads in distribution grids (Kucevic et al., 2021).

Load Balancing: Distributing the load evenly across battery cells to prevent uneven degradation. Active cell balancing techniques distribute charge across individual cells during discharge, reducing imbalances and temperature gradients (Hussein et al., 2023). This approach can significantly enhance cell balance, efficiency, and overall battery system performance (Hussein et al., 2023; Fraccaroli et al., 2024).

2.7 Control algorithms for maximizing the value and performance of lithium-ion batteries

Model Predictive Control (MPC): has emerged as a promising approach for optimizing lithium-ion battery performance and longevity. MPC-based strategies can effectively balance charging time and battery state-of-health (Zou et al., 2018), minimize electrochemical degradation (Castagna et al., 2022), and safeguard cell-level electrochemical limits (Florentino & Trimboli, 2018). These methods often utilize physics-based reduced-order models to capture battery dynamics accurately while maintaining computational efficiency (Xavier et al., 2021). MPC has been applied to various aspects of battery management, including fast charging (Romero et al., 2019), redistributive balancing (McCurlie et al., 2017), and cyclic aging mitigation (Loew et al., 2021). By exploiting internal electrochemical quantities, MPC can control battery performance up to true physical bounds, avoiding conservative voltage-based limits (Xavier et al., 2021).

Adaptive control strategies: have shown promise in maximizing the performance and value of lithium-ion batteries. These approaches can accurately estimate SoC and adapt to parameter variations and thermal uncertainties (Chaoui & Gualous, 2017; Wang et al., 2015). Adaptive controllers can compensate for uncertain parameters and ensure asymptotic stability (Bhavani Sankar Malepati et al., 2018). Neural network-based adaptive controllers have demonstrated near-optimal performance in residential battery systems (Kazhamiaka et al., 2019). Adaptive power management strategies have been successfully implemented in hybrid lithium-ion battery/supercapacitor systems (Sepe et al., 2023). Considering battery aging characteristics in adaptive control design can improve grid-scale battery performance (Parthasarathy et al., 2022). Generalized recursive algorithms allow for more complex battery models in adaptive systems (Verbrugge & Koch, 2006). Receding horizon controllers that adapt to battery age, condition, and SoC have shown superior performance in minimizing operating costs (Allahham et al., 2022).

Fuzzy logic controllers (FLCs): have shown significant potential in optimizing lithium-ion battery performance for EVs and microgrids. FLCs can effectively manage charging and discharging processes, improving battery life, efficiency, and safety (Kushal & Karin, 2015; Liu et al., 2013). These controllers consider factors such as temperature, SOC, and voltage differences to adjust charging currents and balance cell voltages (Martínez et al., 2017; Zaineb et al., 2024). FLCs have demonstrated advantages over conventional methods, including reduced charging time, enhanced charging efficiency, and extended cycle life (Liu et al., 2013). They can also accurately model battery behaviour under various conditions, incorporating temperature effects and SOC estimation (Jiani et al., 2014). Furthermore, FLCs have been applied to multi-switched inductor balancing systems, resulting in faster balancing times and improved pack capacity recovery compared to traditional PI controllers (Cui et al., 2017).

Artificial Intelligence (AI) and Machine Learning (ML): Recent research highlights the significant potential of AI and ML in advancing lithium-ion battery technology. These techniques are being applied across various aspects of battery development, from materials discovery to performance optimization. ML algorithms can accelerate the design and discovery of novel battery materials, including electrodes and electrolytes (Liu et al., 2021; Prasshanth et al., 2024). AI-driven approaches are also proving valuable in battery state estimation, such SOC and SOH, crucial for effective battery management systems (Khawaja et al., 2023; Zheng et al., 2023). Furthermore, AI is enhancing our understanding of electrolyte chemistry and electrode interfaces, which are critical for battery performance and safety (Chen et al., 2023). While challenges remain, the integration of AI and ML in battery research promises to accelerate innovation, improve battery performance, and contribute to the development of more sustainable energy storage solutions (Lv et al., 2021; Faraji Niri et al., 2023; Lombardo et al., 2021).

Kalman Filter and Extended Kalman Filter: The Kalman filter and its variants, particularly the Extended Kalman Filter (EKF), are widely used for estimating the SOC of lithium-ion batteries in EVs and other applications (Rizzello et al., 2021; Shingote et al., 2023). These techniques improve battery performance, safety, and lifecycle by accurately monitoring battery status (Jokic et al., 2018; He et al., 2011). Researchers have developed various models, including the Thevenin model and its improvements, to represent battery characteristics such as hysteresis and polarization (He et al., 2011; Yu & Gao, 2013). Adaptive EKF algorithms have shown superior accuracy compared to traditional EKF, reducing estimation errors significantly (He et al., 2011; Wang et al., 2017). Some studies have also explored other Kalman filter variants, such as the Sigma Points Kalman filter, which demonstrated better performance in handling system non-linearities (Rizzello et al., 2021). Recent advancements have achieved SOC estimation errors of less than 1%, meeting the stringent requirements of battery management systems (Vidya et al., 2023).

3 Hybrid (PV & BEES) System Energy Optimization Model

The chapter presents the system model developed to evaluate and optimize the integration of BESS in power systems. The operational and the technical challenges mentioned in the earlier chapters are addressed. Mainly the SOC, grid tariff, power flow optimization and the grid stability are addressed. It intended to replicate many situations concerning the implementation of BESS in various configurations inside smart grids and microgrids, employing mathematical modelling methodologies and control algorithms. This chapter also includes mathematical derivations to substantiate the analysis.

3.1 System overview

A grid-connected solar PV system serves as the main renewable energy source in the hybrid energy system that makes up the concept. An energy BESS can store surplus solar energy generated during periods of low demand and releasing it when energy demand is high. To evaluate system performance under diverse conditions, various load profiles, representing residential, commercial, and industrial consumers are employed. A centralized EMS is implemented to coordinate power flows between the solar PV system, the BESS, and the electrical grid, thereby ensuring both operational stability and economic efficiency (Byrne, Raymond H., et al. 2017, Li, X., & Wang, S. 2019).

The key components of the system are written on extensively in chapter two which include:

Lithium-ion battery model: A model of the lithium-ion battery is utilized, considering dynamic characteristics such as charge/discharge rates, temperature, and capacity degradation over time Wicke, M., & Bocklisch, T. (2024).

Solar PV model: The solar power system model accounts for varying solar irradiance and temperature conditions, which directly affect PV output.

Power flow model: A power flow analysis is incorporated to determine the distribution of power between the grid, the PV system, and the BESS.

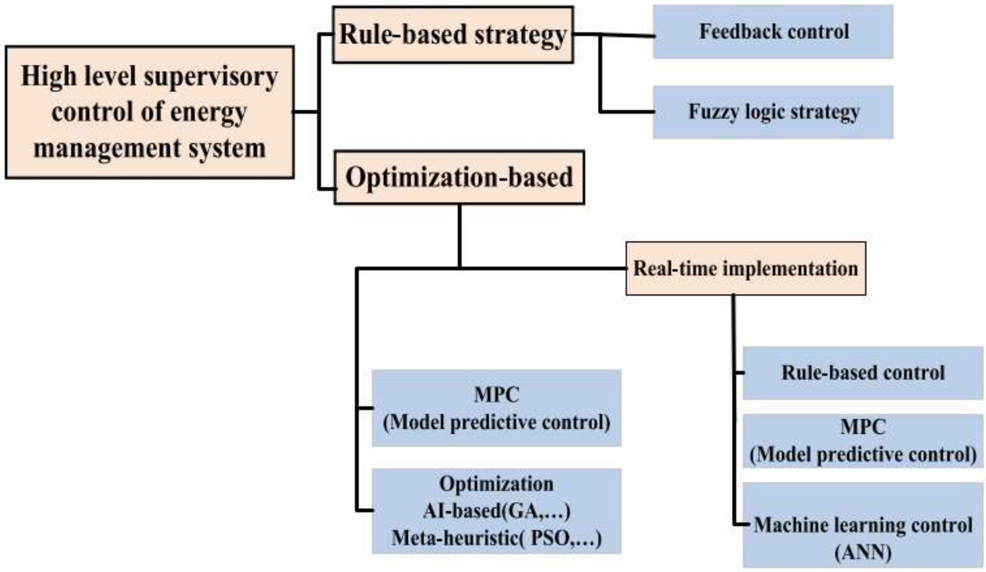

Figure 3**Figure 3.** Categorisation of energy management system of battery–UC Integra-tion.

3.2 The EMS algorithm

An EMS is a smart control framework designed to monitor, control, and optimize the generation, storage, distribution, and consumption of electrical energy. EMS plays a cru-cial role in modern energy systems, particularly in smart grids, microgrids, and buildings equipped with renewable energy sources like solar photovoltaics (PV), wind turbines, and battery storage systems.

At its core, EMS ensures the reliable and cost-effective operation of energy assets, Karami et al. (2020) bal-ancing supply and demand in real time while respecting system constraints such as power limits, state-of-charge boundaries, and operational efficien-cies. It typically uses forecasting data (e.g., load, solar generation), optimization algo-rithms (e.g., Model Predictive Control (MPC), fuzzy logic control (FLC)), and real-time measurements to decide how much pow-er should be drawn from or stored in batteries, taken from the grid, or generated from renewable sources.
MPC is an advanced control strategy that optimizes the future behavior of the system by minimizing a cost function (e.g., minimizing grid power use) over a prediction horizon.

FLC is based on defining rules that mimic human decision-making to control battery operation based on inputs like SOC and load.

We combine the FLC and the MPC to yield a stronger optimization of the EMS. As the FLC is ideal for dealing with rapidly changing conditions, such as unexpected spikes in energy demand or fluctuations in PV power. Its real-time decision-making capabilities ensures that the system responds to dynamic situations quickly and without delay. MPC, on the other hand, offers long-term optimization by utilizing forecasts and restrictions to arrange battery usage and grid interactions over a predictive time horizon. Therefore, the FLC addresses the short-term uncertainty, and MPC ensures that the system runs optimum over time.

Table 1. Implementing of EMS for the main grid, PV, and BESS are described in algorithm 1.

Algorithm 1: EMS for Main, Grid, PV, and BESS

Procedure EMS
    if PV generated is greater than the demand **then**
$Excess_{pv} \longleftarrow P_{pv} - D$
P_{pv}_supplied $\longleftarrow D$
    if SOC <SOC_{max} **then**
$P_{bess} \longleftarrow \min(Excess_{pv}, P_{bess\_max})$
$SOC \mathrel{+}= P_{bess}/Batt_{Cap}$
$P_{grid} \longleftarrow 0$
    else
$P_{grid} \longleftarrow Excess_{pv}$
    else
$P_{pv\_supplied} \longleftarrow P_{pv}$
$Rem_{dem} \longleftarrow D - P_{pv}$
    if SOC > SOC_{min} **then**
$P_{bess} \longleftarrow \min(Rem_{dem}, P_{bess\_max})$
$SOC \mathrel{-}= P_{bess}/Batt_{Cap}$
    else
$P_{grid} \longleftarrow Rem_{dem} - P_{bess}$
    if grid tariff is low **then**
Charge BESS from grid
$P_{grid\_charge} \longleftarrow \min(Excess_{pv}, P_{bess\_max}, SOC_{max} - SOC)$
$SOC + P_{grid\_charge}/Batt_{Cap}$
Return optimized power flow (P_{pv}, P_{bess}, P_{grid})

In the algorithm 1, some condition and decision are made or not made, below are the conditions and the decisions based on different scenarios.

Case 1: When the generated PV is greater than demand

When P_{pv} is greater than D, then the energy demand is supplied by the PV ($P_{pv\_suplied}$ = D). When the SOC is below maximum, the excess PV is used to charge the battery (P_{bess} = min ($excess_{pv}$, P_{bess_max}). When the battery is SOC_{max}, the excess P_{pv} is exported to the main grid. (P_{grid} = $excess_{pv}$-P_{bess}).

These implies:

- No energy is drawn from the grid since the PV is sufficient to meet demand.
- The battery is not discharged in this case because there is no energy deficit.

Case 2: When the generated PV is less than demand

When P_{pv} is less than D, then the energy demand is partly supplied by the PV ($P_{pv\_suplied}$ = P_{pv}). When the SOC is above minimum SOC_{max}, the battery discharge to supply the remaining demand, P_{bess} = min ($Remaining_{demand}$, P_{bess_max}, SOC− SOC_{min}). If the battery cannot meet the deficit or the battery is at the minimum SOC_{min}, power is supplied from the grid for the remaining demand. (P_{grid} = $Reman_{demand}$ − P_{bess}).

Excess PV energy is not exported to the grid because all available PV is used to meet demand.

The battery is not charged in this scenario because there is no surplus energy.

Case 3: When the grid tariff is low ($T_{\_grid}$)

If the grid tariff is low (e.g., during off-peak hours), the battery is charged using grid power to store energy for later use during high-tariff periods (P_{grid_charge} = min (P_{bess_max}, SOC_{max}− SOC).

The SOC of the battery increases as it is charged with grid power. (SOC += $P_{grid-charge}$/$batt_{capacity}$).

This suggests that the battery is not depleted due to the low grid tariff, which makes grid energy more cost-effective. Under this scenario, no electricity is sent to the grid unless there is excess PV energy.

Case 4: When the grid tariff is high

If the grid tariff is high (for example, during peak hours), the battery discharges to fulfill demand rather of using expensive grid electricity (P_{bess} = min (D, SOC−SOC_{min}). Thus, the extra demand that cannot be met with the battery supply are drawn from the grid. (P_{grid}=D−$P_{pv\_supplied}$ − P_{bess}).

These implies that:

- The battery is not charged from the grid in this scenario because the grid tariff is high.
- No surplus PV energy is exported to the grid unless it is unavoidable (e.g., battery is already full, and PV output exceeds demand).

Case 5: Battery at maximum SOC_{max}

If the battery SOC reaches its maximum allowable level (SOC_{max}), it stops charging to avoid overcharging and battery damage (P_{bess} = 0). The excess PV energy that cannot be stored in the battery is exported to the grid (P_{grid} = $excess_{pv}$).

- The battery is not charged further since it has reached its capacity.
- Grid power is not used to meet demand unless there is an energy deficit.

Case 6: Battery at minimum SOC_{min}

If the battery SOC falls to its minimum allowable level (SOC_min), it stops discharging to avoid deep discharge, which could damage the battery (Pbess=0). If demand exceeds PV output, the grid supplies the remaining energy (P_{grid} = D − P_{pv}).

Thus, the battery is not discharged further since it has reached its minimum capacity.

The battery is not charged in this scenario unless there is excess PV energy or low grid tariffs.

Table 2. Summary of Algorithm 1

Scenario	PV to demand	PV to battery	PV to grid	Battery discharge	Grid usage

High PV > demand	Yes	Yes (if SOC < max	Yes (if battery is full)	No	No
Low PV < demand	Yes	No	No	Yes (if SOC > min)	Yes (for deficit)
Low grid tariff	Yes	Yes	No	No	Yes
High grid tariff	Yes	No	No	Yes (if SOC > min)	Yes (if needed)
Battery at soc max	Yes	No	Yes	No	No
Battery at soc min	Yes (if available)	No	No	No	Yes (if deficit)

Table 3. Algorithm 2: EMS with MPC and fuzzy logic for the BESS control

Algorithm 2: EMS with MPC and fuzzy logic for the BESS control

1: Procedure EMS (P_{pv}, D, SOC, T_{grid}) input: P_{pv}, D, SOC, Grid tariff

2: Inputs to fuzzy logic:

Current SOC, P_{pv}, D, and Tgrid

3: Fuzzy rules:

if SOC is low and the P_{pv} > D, **then** charge the battery using excess PV energy

if SOC is high and D > P_{pv}, **then** discharge the battery to meet the demand.

if T_{grid} is low and SOC is not full, **then** charge the battery from the grid to save cost.

if SOC is high and the T_{grid} is high, **then** discharge the battery to reduce grid usage.

4: Output from fuzzy logic

Preliminary control actions for the BESS (P_{bess_fuzzy}).

Step 2: MPC for predictive optimization

11: Input the MPC

12: Forecast data: $P_{pv\_forecast}$, $D_{forecast}$ $T_{grid\_forecast}$

13: Battery constrains: SOC_{min}, SOC_{max}, P_{bess_max}, P_{bess_min}

14:

15. **Optimization objective**

16. Minimize operational costs over a predictive horizon by:

17. Efficiently using the battery to avoid high tariffs.

18 Managing PV utilization to reduce curtailment.

19: **Output from MPC**

20: Optimized power flows: P_{bess_mpc}, P_{pv}, P_{grid}

3.3 Mathematical formulation

In formulating the mathematical derivatives of the model, several key equations and algorithms are considered.

Battery dynamics: The SOC of the BESS is modelled as a function of the charging and discharging rates. Where the SOC at time t is written as [6]

$$SOC(t) = SOC(t-1) + \frac{\eta_c \times P_{charge}(t) - P_{discharge}(t)}{C_{batt}} \quad (1)$$

where,

$SOC\ (t)$ is the state of charge at time t,

η_c is the charge efficiency,

$P_{charge}\ (t)$ is the power flowing into the battery at time t,

$P_{discharge}\ (t)$ is the power discharged from the battery at time t, C_{batt} is the battery capacity.

Solar PV output: The solar PV output is modelled based on the equation giving as

$$P_{PV}(t) = A_{PV} \times G(t) \times \eta_{PV} \quad (2)$$

where,

$P_{PV}\ (t)$ is the power generated by the PV system at time t,

A_{PV} is the area of the PV panels,

$G\ (t)$ is the solar irradiance at time t,

η_{PV} is the efficiency of the PV system.

Grid interaction and power balance: The system always ensures power balance, with the following constraint:

$$P_{load}(t) = P_{grid}(t) + P_{BESS}(t) + P_{PV}(t) \quad (3)$$

where,

$P_{load}\ (t)$ is the power demand at time t,

$P_{grid}\ (t)$ is the power supplied by the grid at time t,

$P_{BESS}\ (t)$ is the net power from the BESS (charging or discharging),

$P_{PV}(t)$ is the solar PV generation.

Optimization objective: The system is optimized to minimize the cost of energy, subject to operational constraints such as battery capacity limits and grid stability. The objective function is,

$$min \sum_{t=1}^{T} (C_{grid} \times P_{grid}(t) + C_{BESS} \times P_{BESS}(t)) \quad (4)$$

where:

C_{grid} is the cost of energy from the grid,

C_{BESS} is the operational cost of the BESS,

T is the total time horizon of the simulation.

3.4 Control algorithms

To ensure optimal performance, the following control strategies are employed:

3.4.1. Model predictive control (MPC)

A model predictive control method is used to regulate the real-time distribution of energy from the BESS, guaranteeing the system functions within physical limitations while reducing energy expenses. MPC improves energy dispatch by minimizing a cost function (e.g., grid power consumption) while accounting for future system states and physical restrictions (e.g., battery capacity, charge/discharge limits).

The goal of MPC is to minimize the grid power usage over a time horizon:

$$min \sum_{t=1}^{T} P_{grid}(t) \quad (5)$$

where,

$P_{grid}(t)$ is the power supplied by the grid at time t,

T is the total number of time steps over the prediction horizon.

This function is subject to several constraints, such as power balance, SOC limits, and battery operational limits.

The total load must always be met by the combination of grid power, battery power, and solar generation.

$$P_{load}(t) = P_{grid}(t) + P_{batt}(t) + P_{solar}(t) \quad (6)$$

where,

$P_{\text{load}}(t)$ is the total load at time t,

$P_{\text{batt}}(t)$ is the power supplied by or absorbed by the BESS,

$P_{\text{solar}}(t)$ is the solar power output at time t.

The SOC of the battery is updated at each time step as a function of the charging or discharging power.

$$SOC(t) = SOC(t-1) + \eta_c * P_{batt}(t) \quad if\ P_{batt}(t) \geq 0 \tag{7}$$

$$SOC(t) = SOC(t-1) - \frac{P_{batt}(t)}{\eta_d}\ if\ P_{batt}(t) < 0$$

(8)

where,

ηc is the charge efficiency,

ηd is the discharge efficiency,

$P_{\text{batt}}(t)$ is the battery power at time t (positive for charging, negative for discharging).

The SOC of the battery is constraint that, it must remain within the limits of the battery capacity. Thus,

$$0 \leq SOC(t) \leq Capacity \tag{9}$$

This ensures that the battery is neither overcharged nor depleted below its minimum allowed SOC.

3.4.2 Fuzzy Logic Control (FLC)

Fuzzy logic is applied to optimize the charging and discharging processes of the BESS based on real-time SOC, load demand, and solar generation.

FLC doesn't rely on traditional mathematical optimization equations but instead applies if-then rules based on fuzzy logic. The SOC and the load demand are classified as the inputs and the battery dis/charging as the output.

Fuzzy inputs

SOC: Ranges from 0 to 100% and is categorized into low, medium, and high. Thus the SOC has three membership functions as $SOC_{\text{low}}(t)$, $SOC_{\text{medium}}(t)$, $SOC_{\text{high}}(t)$.

Load Demand: Ranges from 0 kW to the maximum load and is categorized into low, medium, and high. Three membership functions represent the load demand, $Loadl_{ow}(t)$, $Load_{medium(}t)$, $Load_{high}(t)$.

Fuzzy output (Battery Charge/Discharge): The output is the battery output power (charge/discharge), which can take the values of charging, neutral, or discharging. Battery output charge (t), battery output neutral (t), battery output discharge(t).

Fuzzy Logic Rules:

The behavior of the BESS is controlled by fuzzy if-then rules. The rules are

Rule 1: If $SOC_{low}(t)$, and $Load_{high}(t)$, then battery output charge(t).

Rule 2: If $SOC_{high}(t)$, and $Load_{high}(t)$ then battery output discharge (t).

3.5 Conclusion

This chapter has provided a detailed description of the system model used to analyze the integration of BESS into power systems. The mathematical formulations, control algorithms, and key assumptions have been presented to form the basis for the simulation and optimization efforts, which will be covered in Chapter Four.

4 Result and analysis

4.1 Introduction

This chapter presents the simulation of the system model described in Chapter Three. The simulations are implemented in Python using Jupyter Notebook, which is well-suited for data analysis and visualization. The objective of the simulations is to evaluate the performance of the BESS in conjunction with a solar PV system under different scenarios, including varying load profiles and solar irradiance conditions. The simulations also test the effectiveness of control algorithms such as MPC and FLC in optimizing the operation of the BESS.

4.2 Simulation setup

Jupyter Notebook is used to provide an interactive simulation experience in a Python environment. Important Python libraries include scipy for sophisticated optimization algorithms, pyomo for implementing MPC, skfuzzy for creating FLC techniques, numpy for effective numerical operations, and matplotlib for data displays. To closely replicate real-time operating circumstances, the simulations are run over a 24-hour period at 15-minute intervals. A synthetic dataset is employed for the purposes of this study, giving room for controlling variable under different circumstances. Solar irradiance data from a typical sunny day, load profiles representing residential, commercial, and industrial energy consumption are some features of the data. The specifications for the lithium-ion battery, includes capacity, charge/discharge efficiency, and degradation rates.

4.3 Simulation analysis

This section presents simulations as well as descriptions of the scenarios involved in EMS optimization. The results of the analysis are also provided, along with deductions and interpretations.

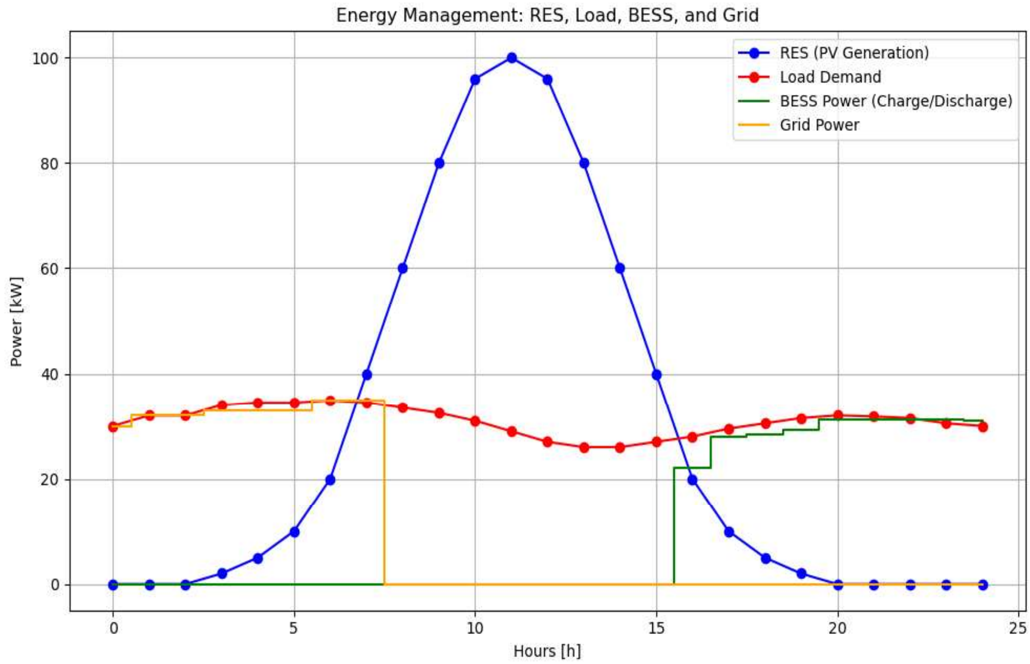

Figure 4a. Depicts the characteristics of the PV, load demand, BESS and the grid

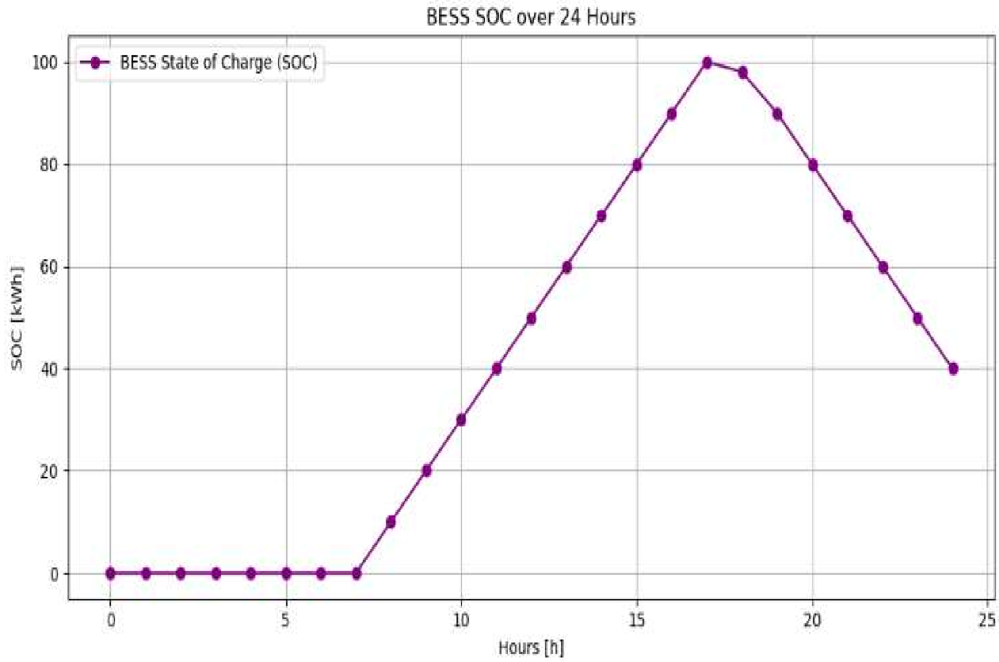

Figure 4b. Depicts the BESS SOC considering the PV, load demand, BESS and the grid

Figure 4a outlines EMS power coordination among PV, BESS, load, and grid. PV generation peaks midday (07:00–15:00) as a bell curve, while load demand remains stable. BESS charges during PV surplus and discharges during PV deficits, optimizing self-consumption. Grid reliance peaks in non-PV hours but intermittently recurs midday, likely reflecting economic temporal arbitrage (e.g., low-tariff grid charging). The system prioritizes renewable utilization while balancing grid cost efficiency.

Figure 4b shows the SOC dynamics of the BESS, highlighting its daily cycle. From 07:00–16:00, rapid charging via PV surplus raises SOC to 90 kWh. Post-hour 16, declining PV triggers discharge to offset generation deficits, reducing SOC by the end of the day. The profile underscores the EMS's energy strategy, deep discharge during low/no PV and aggressive charging during peak PV availability.

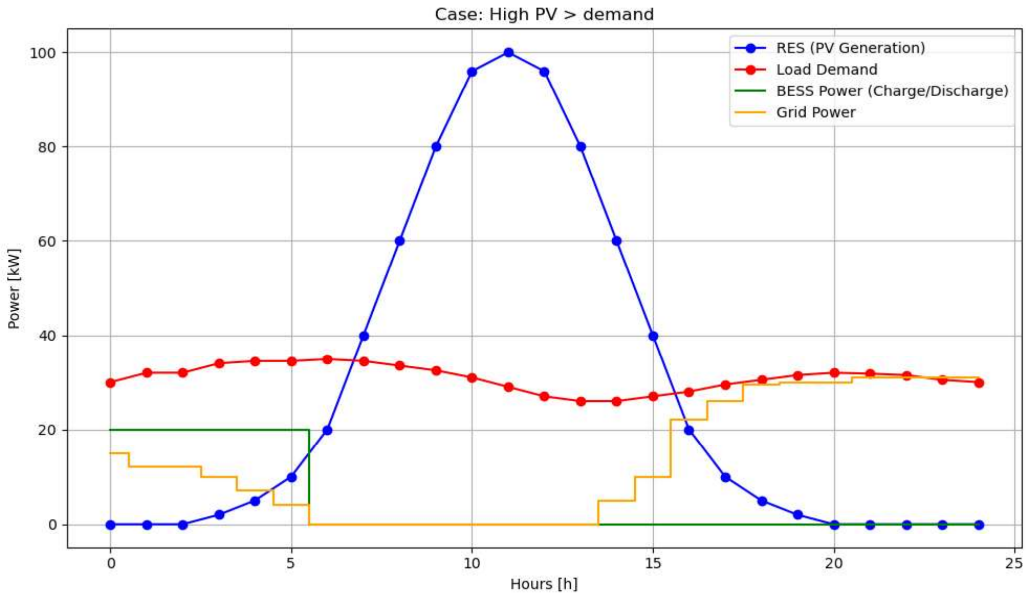

Figure 5a. Depicts the high PV greater than demand

Figure 5a illustrates energy flow dynamics when PV generation exceeds the load demand. The PV curve (blue) peaks midday, contrasting with the load profile (red), creating significant daytime surplus (08:00–15:00). Excess energy generated by the PV system is directed to the BESS (green) for storage. Grid import (orange) indicates that electricity is being drawn from the main grid, typically due to favourable tariff conditions. During periods when PV generation and BESS supply are insufficient, the main grid is utilized to meet the remaining load demand.

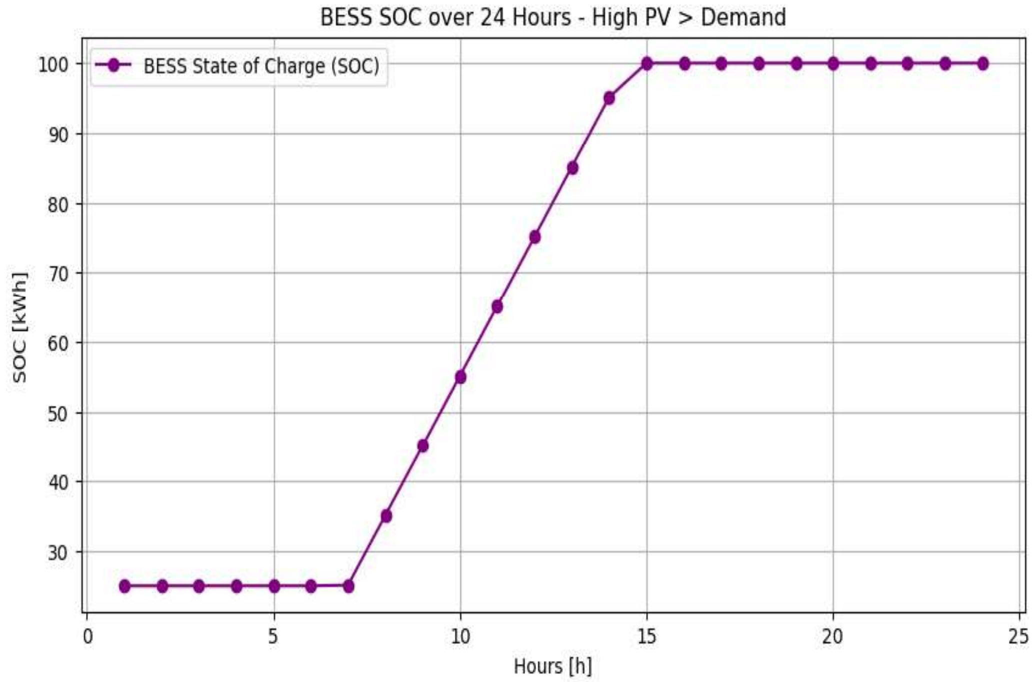

Figure 5b. Depicts the BESS SOC considering the PV is greater than demand.

Figure 5b analyzes the BESS SOC profile under surplus PV conditions. Starting at 15%, SOC remains stable overnight (00:00–07:00), indicating minimal discharge and grid reliance. From 07:00–15:00, excess PV rapidly charges the BESS to 100% capacity. Post-saturation, the surplus of PV is transmitted to the grid or for direct consumption. The absence of discharge cycles post-charge suggests low nighttime demand, alternative grid imports, or operational constraints to avoid deep discharge.

Figure 6a below demonstrates EMS operation under persistent PV generation deficits relative to load demand. The PV curve (blue) is less than the load demand (red) during the time interval 0 to 7 hrs and 16-25 hrs, creating a continuous energy shortfall. The BESS (green) discharges to offset the supply deficit. Grid power (orange) compensates for the shortfall, exhibiting stepwise import patterns, suggesting hierarchical control logic that prioritizes local resources (PV/BESS) before activating incremental grid imports.

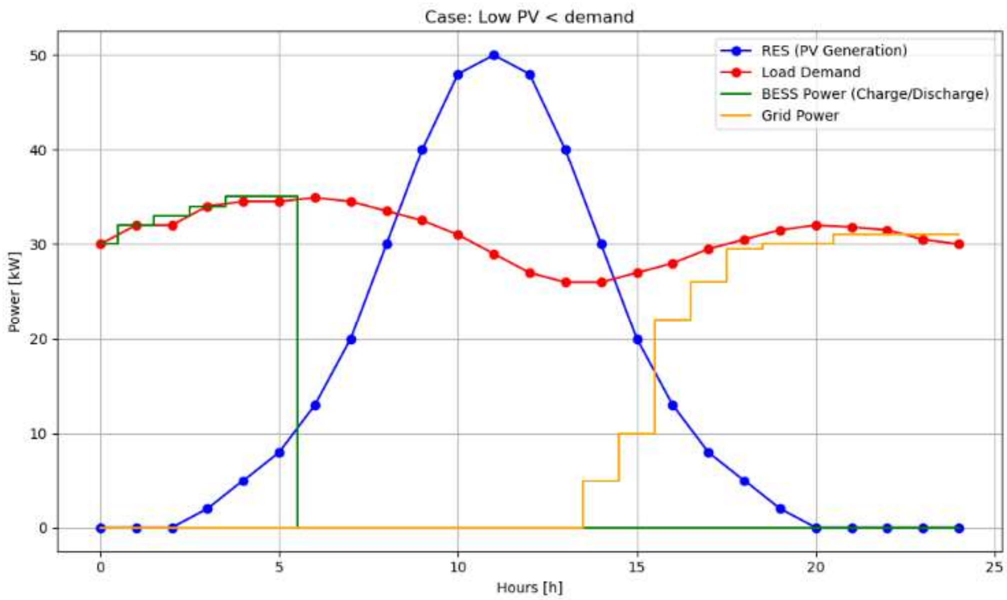

Figure 6a. Depicts the low PV generated

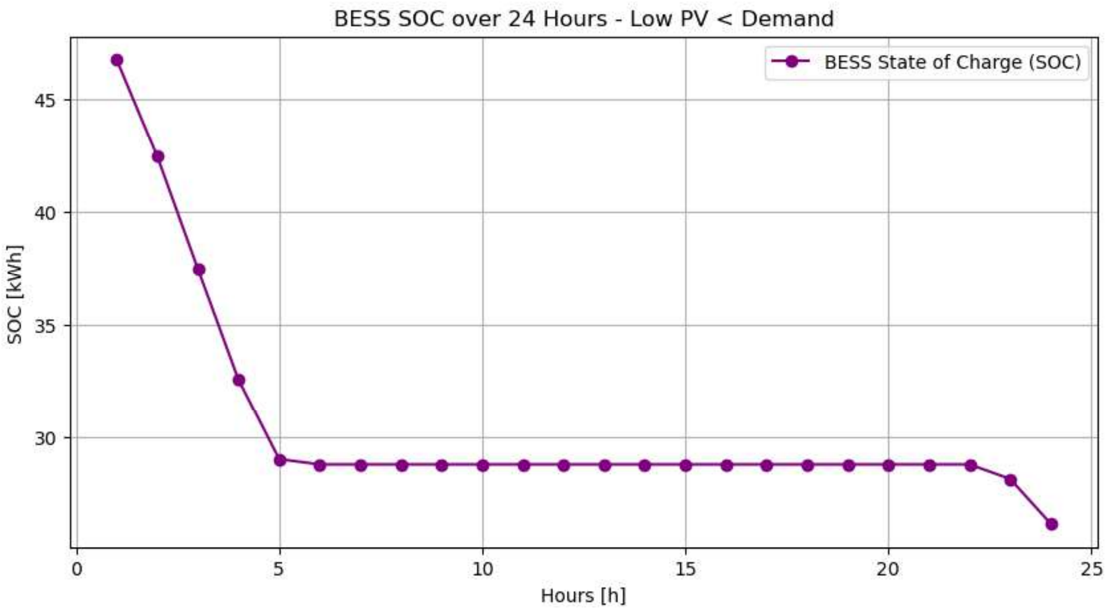

Figure 6b. Depicts the SOC when the PV generate less power.

Figure 6b above illustrates the SOC dynamics of the BESS under conditions of persistent PV generation shortfalls relative to load demand. The SOC begins at 47 kWh but depletes by hour 5 due to discharge cycles compensating for the PV deficit, after which it remains at 27kWh for the remaining 19 hours.

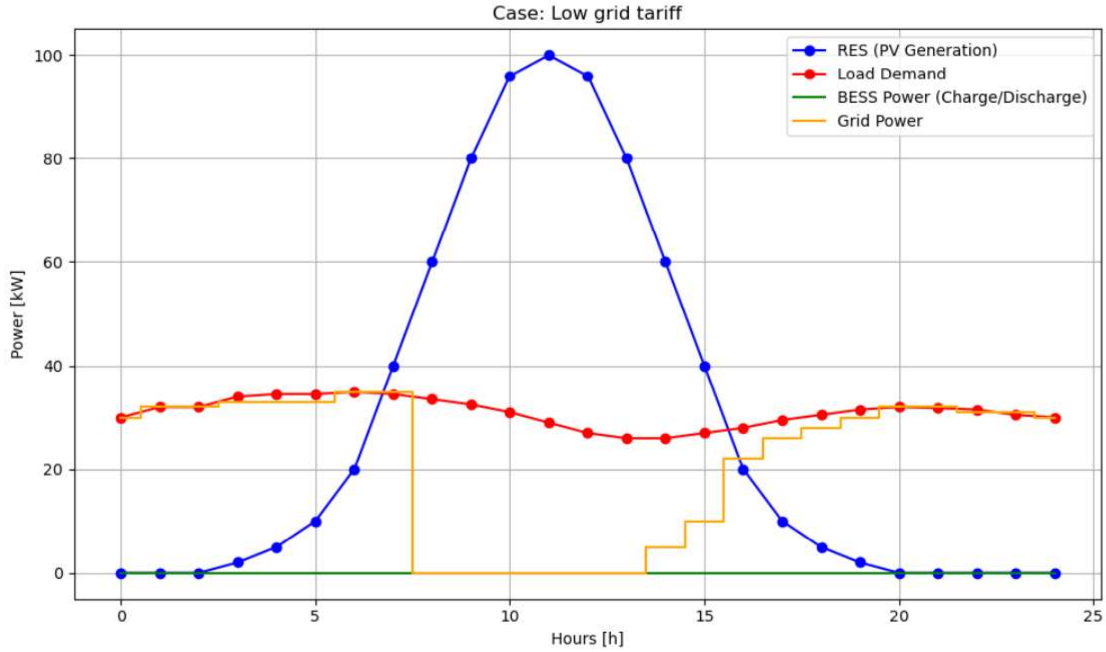

Figure 7a. Depicts when the grid tariff is low

Figure 7a depicts an EMS where there are available PV and main grid are at a cheaper tariff. The PV curve (blue) exhibits a normal bright day profile, peaking midday remaining above the stable load demand (red), resulting in a continuous energy availability. Grid power (orange) compensates for the deficit, particularly during low/no PV periods (early/late hours). This strategy gives the BESS room to charge.

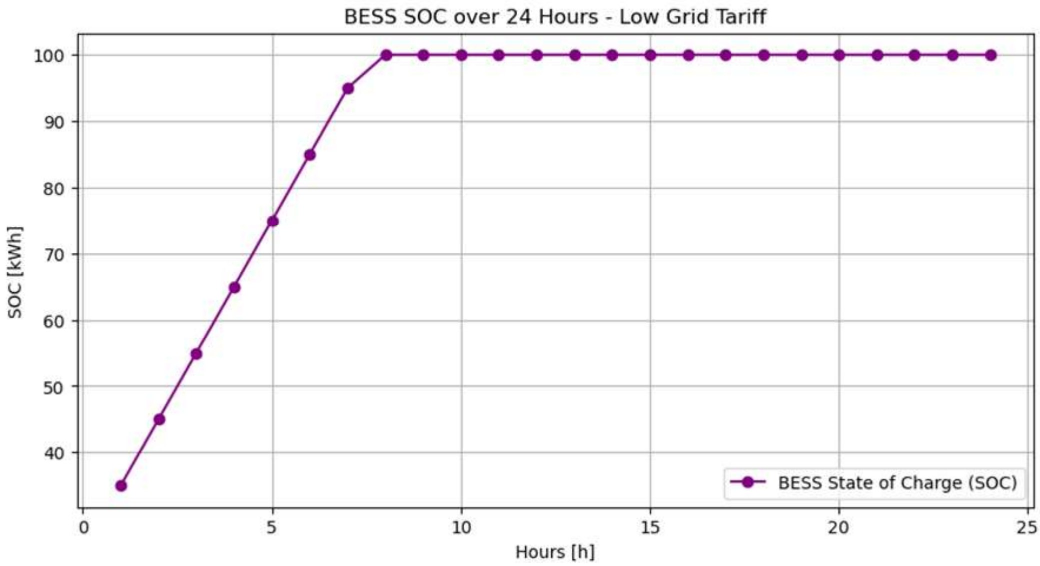

Figure 7b. Depicts the BESS SOC when the grid tariff is low

Figure 7b above illustrates the SOC dynamics of the BESS when there is excess PV power available after meeting the load demand. This surplus PV power is subsequently utilized to charge the battery, resulting in an increase in the SOC. Specifically, the SOC rises from an initial level of 35 kWh to a full capacity of 100 kWh over the course of a few hours.

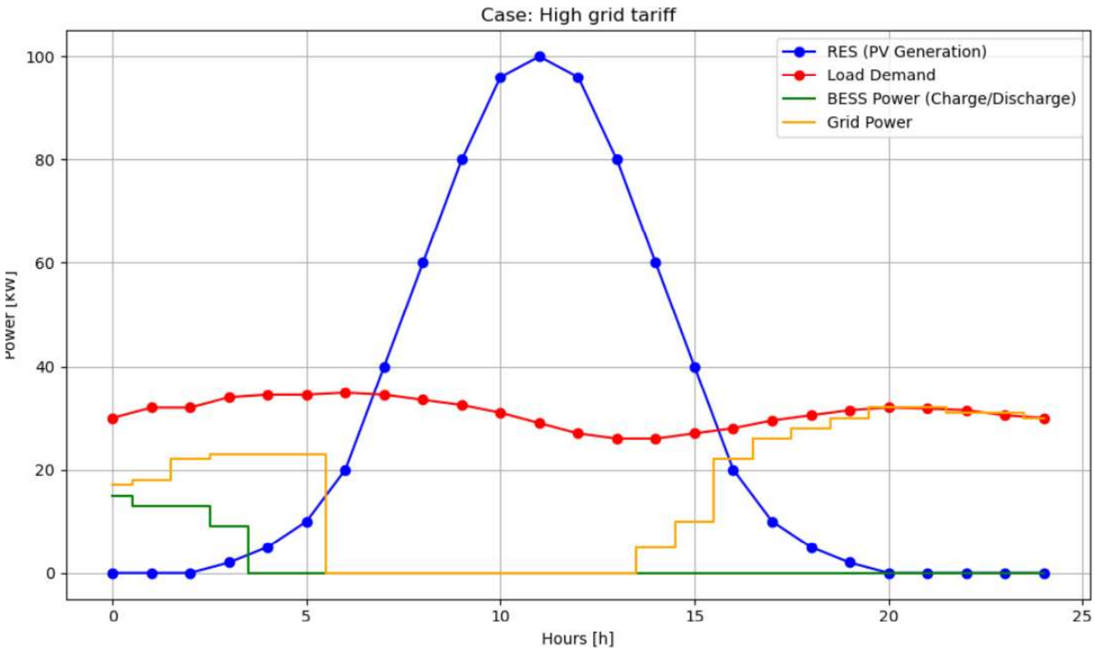

Figure 8a. Depicts when the grid tariff is high

Figure 8a outlines the EMS power flow dynamics under a scenario prioritizing grid tariff avoidance. The PV generation (blue curve) follows a bell-shaped profile peaking midday (08:00–15:00), while load demand (red curve) remains stable with minor daily variations. The EMS minimizes excess grid reliance (orange curve), avoiding high-tariff periods by discharging the BESS (green curve) during early morning (00:00–06:00). Unlike scenarios leveraging grid charging, the BESS discharges exclusively to offset grid imports, reflecting a cost-optimized strategy. Key observations include dual reliance on grid and BESS during pre-dawn hours (00:00–06:00), indicating partial storage capacity to meet full demand.

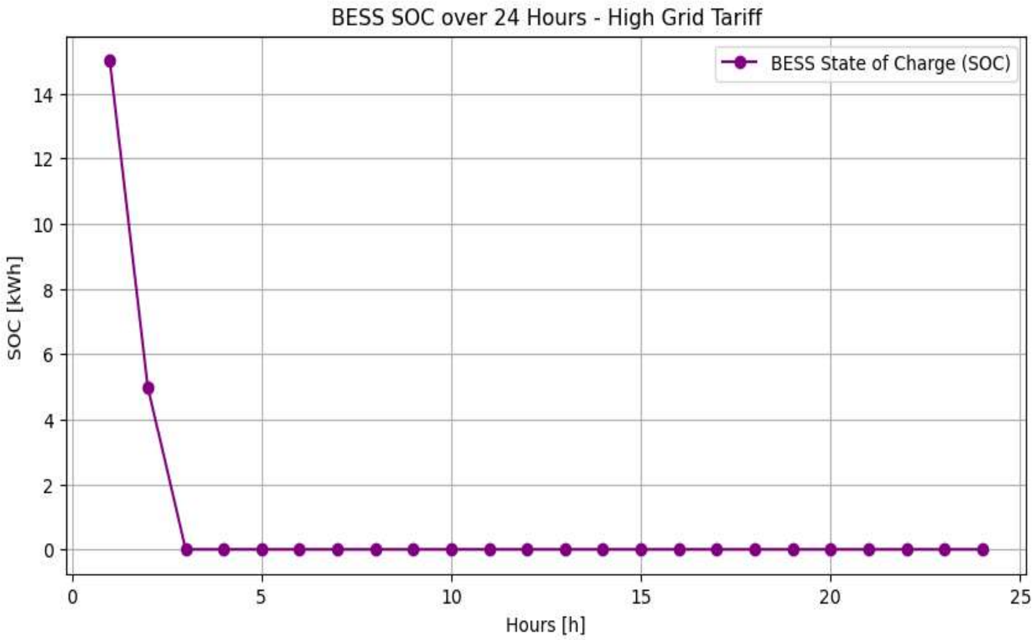

Figure 8b. Depicts the BESS SOC when the grid tariff is high

Figure 8b above illustrates the SOC trajectory of the battery BESS under high-tariff grid conditions, emphasizing cost-driven operational constraints. The SOC initiates at 15 kWh but depletes fully by hour 5 due to prioritized discharge cycles to avoid high-cost grid imports. Post-depletion, the SOC remains at zero for the remaining 19 hours, reflecting no charging activity, neither from the grid (due to tariff avoidance) nor from PV.

This contrasts with scenarios where midday PV surpluses recharge the BESS, highlighting a rigid cost-minimization strategy that sacrifices storage cycling to eliminate tariff-associated charging costs. The absence of SOC recovery underscores two critical factors: (1) PV generation is entirely consumed by the load, leaving no excess for storage, and (2) grid charging is economically disincentivized. The system thus operates without storage buffering, relying solely on real-time PV and grid power.

Figure 9a below depicts the temporal dynamics of power flow within EMS, analyzing the interplay between PV generation, load demand, BESS operation, and grid interaction. The PV output (blue trace) exhibits a characteristic daily profile, peaking at midday (08–15 hours) due to PV irradiance patterns, while the load demand (red trace) demonstrates a steady-state profile with nominal fluctuations, decoupled from the solar generation cycle.

The BESS power flow (green trace) reveals constrained charging activity, with the system attaining its SOC threshold early in the operational cycle. The excess PV generation is used directly to supply demand as evidenced by the near-zero grid power utilization (orange trace). This underscores the EMS's transient self-sufficiency under optimal solar conditions.

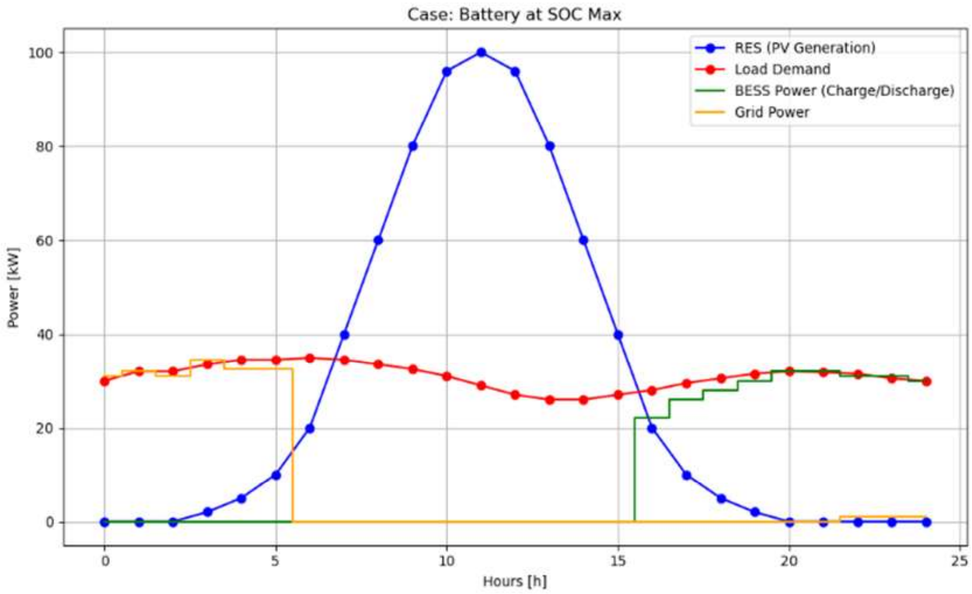

Figure 9a. Depicts the temporal dynamics of power flow within EMS

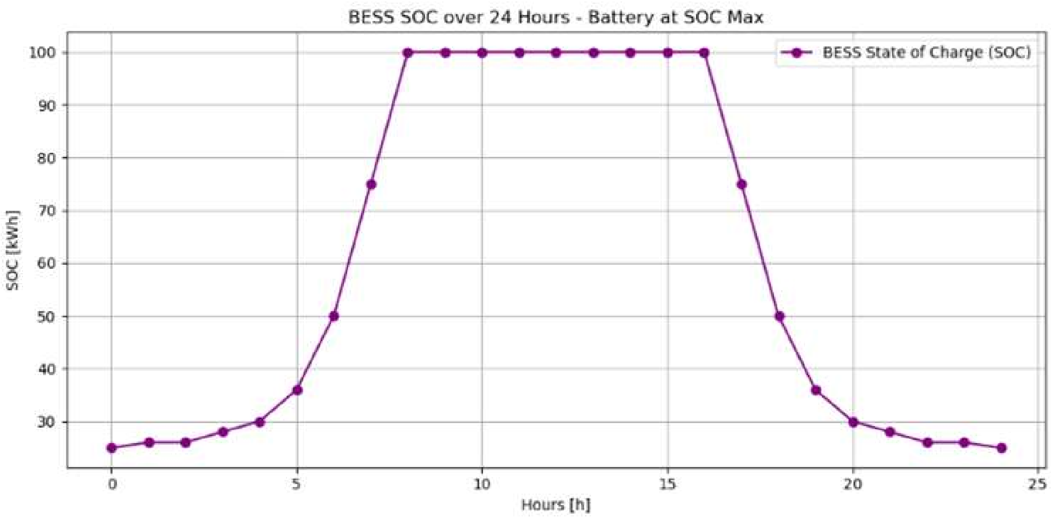

Figure 9b. Depicts the BESS SOC at maximum

Figure 9b above shows the SOC dynamics of the BESS, illustrating its charge-discharge cycling and operational thresholds under PV-driven conditions. The SOC profile initiates at a suboptimal baseline (25 kWh), reflecting partial pre-dawn charge retention. During low-irradiance intervals (pre-hour 6), incremental charging occurs via residual PV yield, transitioning to rapid SOC escalation as solar irradiance intensifies, achieving full saturation (100% SOC) by hour 8. Post-saturation, the SOC curve, signifying charge termination despite continued PV surplus, a critical constraint in energy arbitrage efficiency.

Overall, these results demonstrate the challenges and opportunities of operating an EMS when the BESS is at maximum SOC. The battery effectively captures surplus energy early in the day, but once full, it no longer contributes to system flexibility. This scenario underscores the importance of implementing advanced control strategies, such as dynamic load shifting, additional storage expansion, or optimized grid export mechanisms, to ensure that excess PV energy is fully utilized. Also, the system's reliance on direct PV consumption rather than stored energy indicates a well-balanced operational mode that prioritizes renewable utilization while minimizing grid dependence.

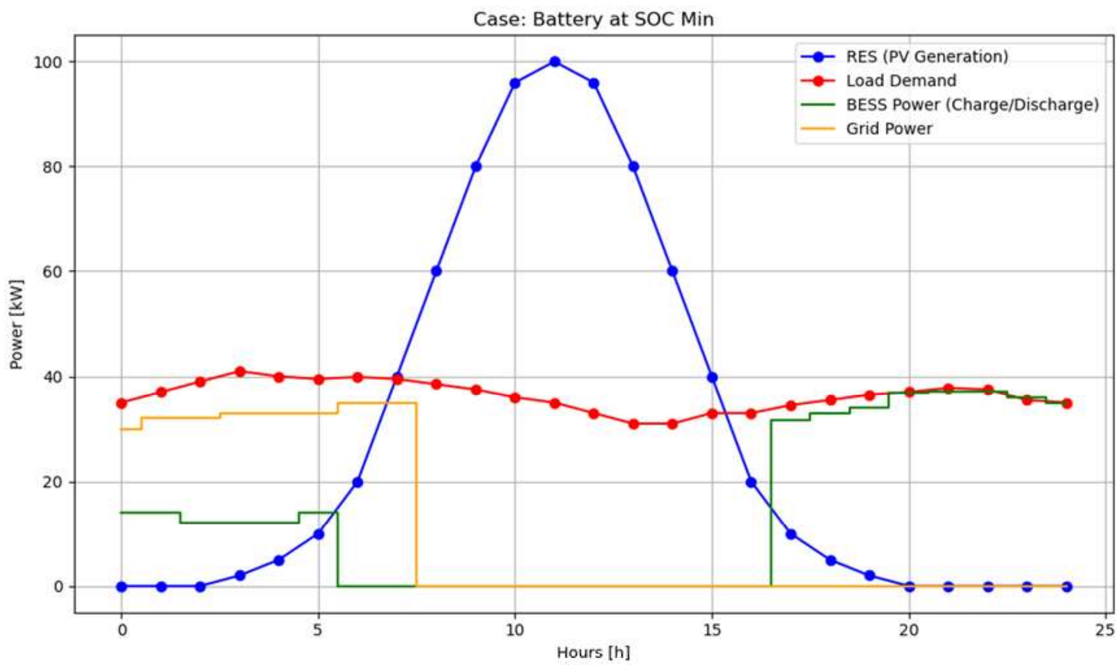

Figure 10a. Illustrates EMS power flow dynamics

Figure 10a above illustrates EMS power flow dynamics in a scenario characterized by PV generation-demand mismatch and constrained BESS capacity. The PV curve (blue) follows a daily bell-shaped profile, peaking midday (08:00–15:00), while load demand (red) remains stable, creating intermittent surpluses and deficits relative to solar availability. The BESS (green curve) discharges minimally in early morning hours but depletes rapidly due to low initial SOC rendering it inactive post-depletion (SOC = 0). This forces significant grid reliance (orange curve) during pre-dawn. In the evening periods when PV generation is insufficient the BESS supplied the load demand.

The profile emphasizes the need for BESS capacity scaling, SOC optimization, or demand-side management (e.g., load shifting to align with PV peaks) to reduce grid reliance and enhance resilience in energy systems with temporally mismatched generation and consumption patterns.

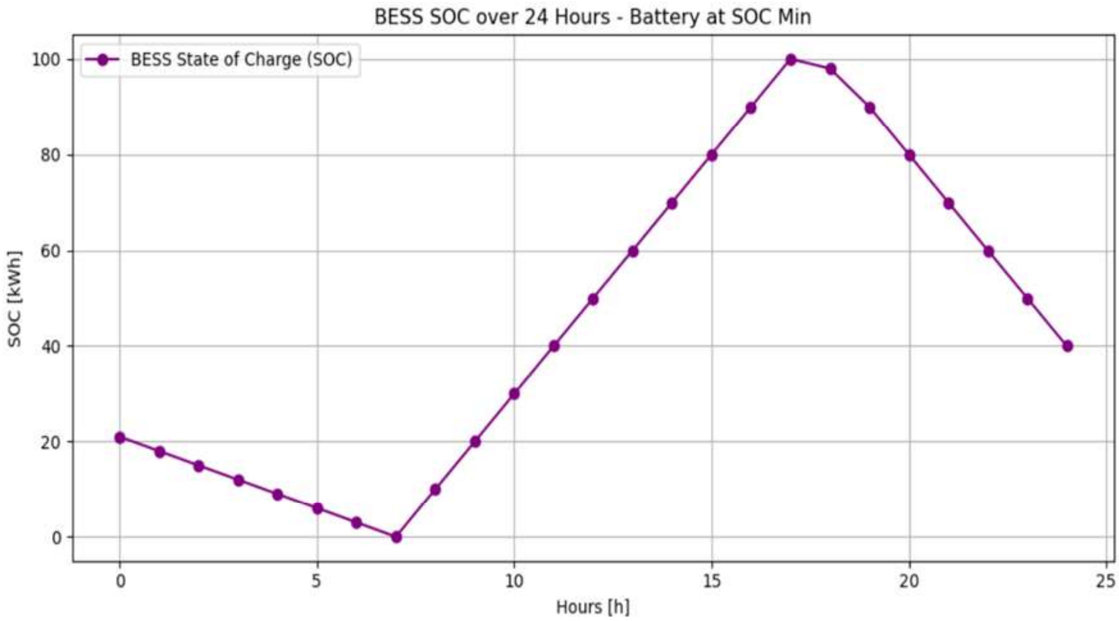

Figure 10b. Depicts the SOC profile of the BESS under conditions of constrained

Figure 10b illustrates the behaviour of the BESS when it starts at its minimum SOC. For the first 5 hours (from 0 to 5 hours), the SOC discharged to supply the load demand. From hour 7 to around hour 17, the SOC increases sharply in a linear fashion, rising from 0 kWh to approximately 100 kWh. This rapid increase suggests that surplus PV power, after meeting the load demand, is being used to charge the battery. The steep slope indicates a high charging rate, and the battery reaches its maximum capacity of 100 kWh within this 10-hour window.

Starting from hour 19, the SOC begins to decrease steadily, dropping back down to around 35 kWh by hour 24. This gradual decline suggests that the battery is now discharging to supply power to the load.

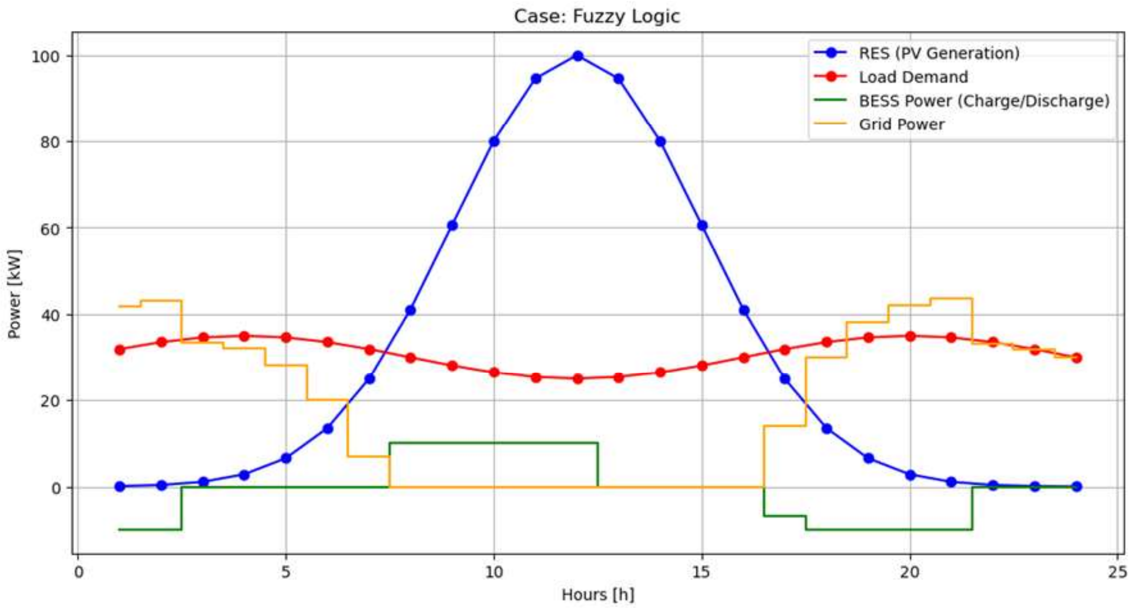

Figure 11a. Demonstrates EMS operation enhanced by a FLC

Figure 11a above demonstrates EMS operation enhanced by a FLC, optimizing power flow dynamics among PV generation, BESS, load demand, and grid interaction. The PV curve (blue) exhibits a bell-shaped midday peak (10:00–15:00), while load demand (red) remains stable, creating temporal mismatches between generation and consumption. The BESS (green curve) operates dynamically under FLC governance: discharging during early low-PV hours to minimize grid reliance and transitioning to gradual charging as solar generation rises, avoiding abrupt power swings.

Grid usage (orange curve) follows a stepwise, adaptive pattern, activated only when PV and BESS capacities are insufficient, reflecting the FLC's real-time prioritization of local resources over grid imports. This contrasts with previous scenarios with rigid grid dependency or storage underutilization. The FLC's nuanced decision-making reduces operational inefficiencies, balances economic costs (e.g., minimizing high-tariff grid imports), and enhances resilience by smoothing transitions between energy sources.

The profile underscores the efficacy of intelligent control systems in reconciling intermittent renewables, storage limitations, and load variability. By dynamically adjusting charge/discharge rates and grid interaction, the FLC mitigates demand-supply mismatches, curtails peak grid reliance, and optimizes storage utilization—showcasing advancements overrule-based strategies in achieving techno-economic efficiency in hybrid renewable energy systems.

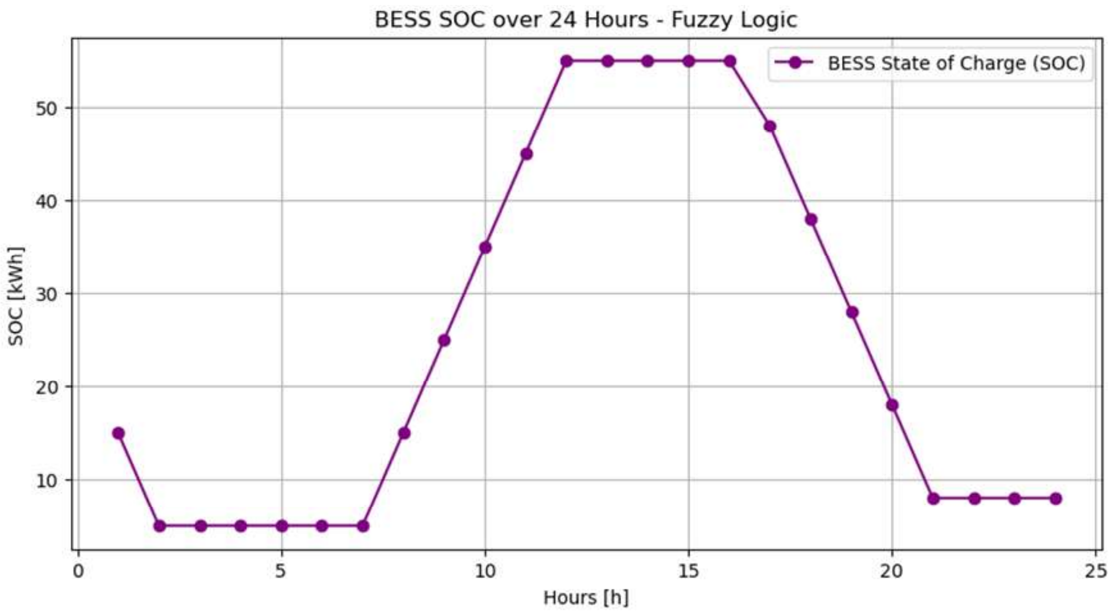

Figure 11b. Shows the SOC dynamics of the BESS governed by a FLC

Figure 11b delineates the SOC dynamics of the BESS governed by a FLC. The SOC initiates at 15 kWh, declining during pre-dawn hours (00:00–05:00) as the BESS discharges to meet demand, with FLC maintaining a reserve capacity to prevent deep discharge and ensure emergency readiness. From 08:00–15:00, SOC move upward smoothly to 100% through controlled charging during peak PV generation, avoiding abrupt power transitions. Post-17:00, SOC decreases incrementally to offset evening demand, yet FLC enforces a minimum SOC threshold to preserve battery lifespan and operational resilience.

This adaptive strategy contrasts with rigid rule-based approaches, demonstrating FLC's efficacy in harmonizing real-time PV-load mismatches with storage longevity. The gradual charge/discharge modulation optimizes temporal energy arbitrage, minimizes grid reliance, and mitigates degradation risks, exemplifying advanced control's role in enhancing techno-economic performance of renewable-storage hybrid systems.

Overall, these results demonstrate the effectiveness of fuzzy logic in managing energy storage and optimizing grid interactions. Unlike fixed rule-based strategies, fuzzy logic provides a more adaptive approach, ensuring that battery charging and discharging decisions are made dynamically based on real-time conditions. This leads to improved energy efficiency, reduced reliance on the grid, and better utilization of available PV.

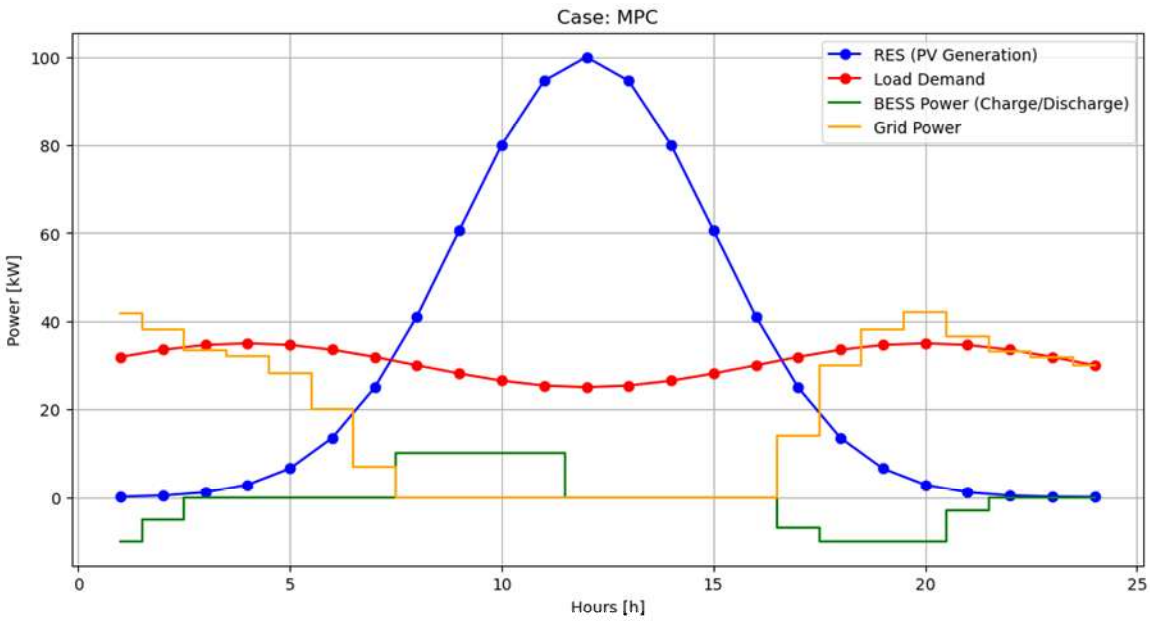

Figure 12a. Illustrates EMS operation governed by MPC

Figure 12a above illustrates EMS operation governed by MPC, optimizing power flow via anticipatory scheduling of BESS and grid interaction. The BESS (green curve) follows a preplanned charging/discharging scheme: charging during high PV generation (06:00–12:00) to harness solar surpluses and discharging post-12:00 to offset evening demand, aligning with predicted PV unavailability.

Grid power usage (orange curve) is strategically restricted to low-tariff periods (early morning/evening), reflecting MPC's economic prioritization of cost-minimized grid imports. The MPC proactively balances real-time actions with forecasted generation-demand profiles across its operational horizon. The structured BESS cycling and restrained grid reliance demonstrate MPC's capacity to harmonize temporal energy arbitrage, peak tariff avoidance, and storage efficiency.

The profile underscores MPC's superiority in systems requiring long-term optimization, mitigating demand-supply mismatches while ensuring techno-economic efficiency through predictive, rather than reactive, decision-making.

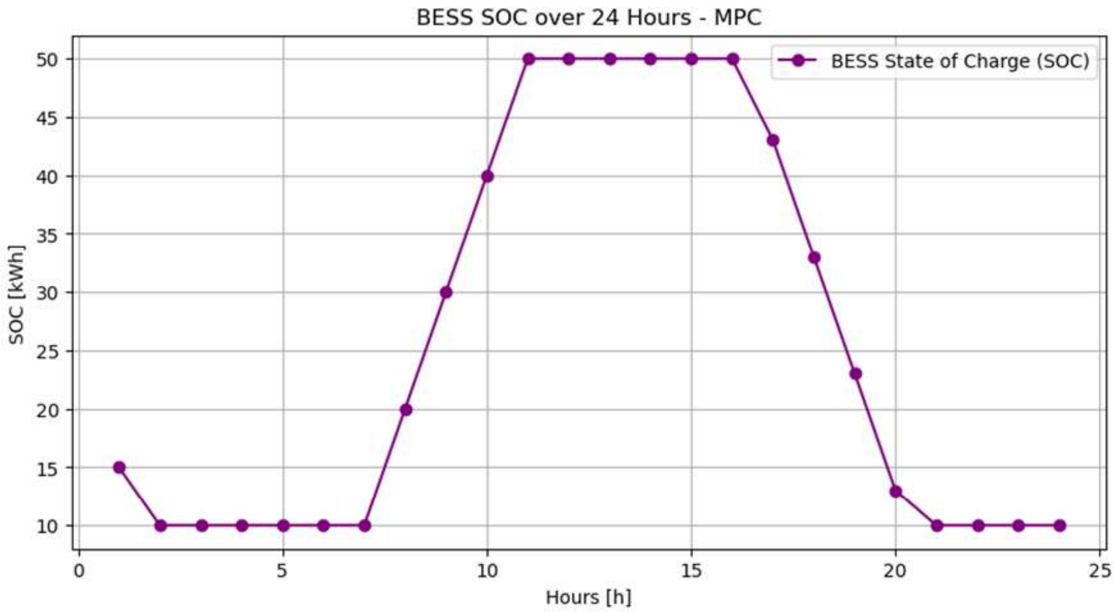

Figure 12b. Depicts the SOC trajectory of the BESS under MPC

Figure 12b above delineates the SOC trajectory of the BESS under MPC, emphasizing anticipatory optimization of storage dynamics. Initialized at ~15 kWh, the SOC retains a minimal reserve threshold, avoiding deep discharge to preserve emergency readiness. During peak PV generation (06:00–12:00), the SOC ascends smoothly to full capacity (50 kWh), reflecting MPC-driven charging aligned with solar surpluses and forecasted demand. Post-16:00, the SOC discharges gradually, distributing energy release to offset evening demand while adhering to predicted load profiles and tariff structures.

By 21:00, the SOC reaches its predefined minimum threshold, demonstrating MPC's capacity to balance storage utilization with battery longevity, thus, preventing degradation from excessive cycling or deep discharge. Unlike rule-based strategies, MPC enforces structured charge/discharge phases, harmonizing daily energy arbitrage with lifecycle constraints. The profile underscores MPC's predictive prowess in aligning storage operation with variable tariffs and generation patterns, achieving cost-efficient grid reliance reduction while extending BESS lifespan through controlled DOD management.

The results underscore MPC as a superior paradigm for EMS, leveraging predictive analytics to optimize power allocation, grid interaction, and storage utilization. By forecasting energy demand and generation, MPC pre-emptively schedules battery charge/discharge cycles and grid imports/exports, aligning operations with economic and technical objectives—minimizing operational costs, curtailing peak tariff grid reliance, and mitigating battery degradation through controlled DOD management.

The findings advocate MPC's integration into modern EMS architectures, particularly in systems prioritizing cost-effective, sustainable renewable integration. By harmonizing predictive optimization with dynamic constraints, MPC advances the viability of resilient, self-sufficient energy systems, setting a benchmark for adaptive control in evolving grid paradigms.

5 Conclusion

5.1 Introduction

This chapter provides a summary of the key findings from this research and offers conclusions based on the results of the system modelling and simulations presented in earlier chapters. Additionally, it outlines the contributions of this study to the integration and optimization of BESS in power grids and discusses recommendations for future research and potential applications in the industry.

5.2 Summary of findings

The integration of BESS within modern power systems has become a pivotal component in addressing the challenges of renewable energy integration and ensuring grid stability. This study explored the technical, operational, and optimization aspects of BESS in various configurations, emphasizing their role in improving grid flexibility and efficiency. Here, we consolidate the main findings, implications, and recommendations drawn from the literature review, system modelling, and simulations.

As explored in Chapter Two, advancements in lithium-ion battery technology have significantly enhanced BESS's suitability for grid applications. Developments in BMS and control algorithms have optimized battery performance and safety, proving essential for effective grid integration and renewable energy management. The research identified operational strategies that can extend battery life, improve efficiency, and reduce costs, which are crucial for maximizing the value of BESS.

The system model in Chapter Three emphasized the complexities involved in incorporating BESS into smart grids and microgrids. Key parameters such as SOC, SOH, power flow, and grid stability were addressed. The model demonstrated that strategic control of these parameters can mitigate common challenges like voltage deviations and frequency instability, underscoring the need for robust energy management systems.

Chapter Four presented a simulation of BESS operations within a solar-powered grid context, highlighting the roles of MPC and FLC in optimizing battery charge/discharge cycles. The simulations showed that these control strategies effectively balance energy supply and demand, reduce reliance on grid power during peak times, and maintain grid stability. The results validated the system model, demonstrating that BESS can efficiently support fluctuating energy demands in a hybrid grid environment.

In conclusion, this study underscores the transformative potential of BESS in creating resilient, flexible, and sustainable power systems. The integration of advanced control strategies and optimized battery management practices can effectively support grid stability while enhancing renewable energy usage. Through continued technological advancements, supportive policies, and a focus on sustainability, BESS can significantly contribute to the transition towards a more robust and green energy infrastructure.

5.3 Future work

Future work will focus on minimizing reliance on the main grid, particularly during peak tariff periods, to effectively meet all established constraints.

References

Li, Y., Feng, B., Li, G., Qi, J., Zhao, D., & Mu, Y. (2018). Optimal distributed generation planning in active distribution networks considering integration of energy storage. Applied Energy, 210, 1073-1081. https://doi.org/10.1016/j.apenergy.2017.08.008

Yi, F., Lu, D., Wang, X., Pan, C., Tao, Y., Zhou, J., & Zhao, C. (2022). Energy management strategy for hybrid energy storage electric vehicles based on pontryagin's minimum principle considering battery degradation. *Sustainability, 14*(3), 1214. https://doi.org/10.3390/su14031214

Sintianingrum, K. (2020). Optimization of microgrid battery capacity using pso with considering islanding operation. *Journal of Engineering and Scientific Research, 2*(1). https://doi.org/10.23960/jesr.v2i1.34

Gür, T. M. (2018). Review of electrical energy storage technologies, materials and systems: challenges and prospects for large-scale grid storage. *Energy & Environmental Science*, *11*(10), 2696-2767.

Zeng, X., Li, M., Abd El-Hady, D., Alshitari, W., Al-Bogami, A. S., Lu, J., & Amine, K. (2019). Commercialization of lithium battery technologies for electric vehicles. *Advanced Energy Materials*, *9*(27), 1900161.

Lipu, M. H., Hannan, M. A., Karim, T. F., Hussain, A., Saad, M. H. M., Ayob, A., ... & Mahlia, T. I. (2021). Intelligent algorithms and control strategies for battery management system in electric vehicles: Progress, challenges and future outlook. *Journal of Cleaner Production*, *292*, 126044.

PS, P. K., Jayalakshmi, N. S., & Kedlaya, A. (2020, July). Energy management strategies for hybrid energy storage system in electric vehicles: A review. In *2020 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT)* (pp. 1-7). IEEE.

Xiong, R., Cao, J., Yu, Q., He, H., & Sun, F. (2017). Critical review on the battery state of charge estimation methods for electric vehicles. Ieee Access, 6, 1832-1843.

Xiang, H., Wang, Y., Li, K., Zhang, X., & Chen, Z. (2023). A comprehensive study on state-of-charge and state-of-health estimation of sodium-ion batteries. Journal of Energy Storage, 72, 108314.

Wan, L., Liu, L., Cai, D., Chen, R., Liu, H., Wang, T., & Li, D. (2022, August). Joint Estimation of State of Charge and State of Health and Fault Early Warning for Energy Storage Power Station based on Double Unscented Kalman Filter Algorithm. In 2022 Power System and Green Energy Conference (PSGEC) (pp. 137-143). IEEE.

Wei, Z., Zhao, J., Xiong, R., Dong, G., Pou, J., & Tseng, K. J. (2018). Online estimation of power capacity with noise effect attenuation for lithium-ion battery. IEEE Transactions on Industrial Electronics, 66(7), 5724-5735.

Huang, Y., Qin, L., & Wu, G. (2021, July). State of health estimation based on constant current charging profiles. In 2021 40th Chinese Control Conference (CCC) (pp. 5899-5904). IEEE.

Zhang, X., Wang, Y., Liu, C., & Chen, Z. (2018). A novel approach of battery pack state of health estimation using artificial intelligence optimization algorithm. Journal of Power sources, 376, 191-199.

Sun, B., Jiang, J., Zheng, F., Zhao, W., Liaw, B.Y., Ruan, H., Han, Z. and Zhang, W., 2015. Practical state of health estimation of power batteries based on Delphi method and grey relational grade analysis. Journal of Power Sources, 282, pp.146-157.

Ibrahim, H., & Ghandour, M. (2018). Optimization of energy management of a microgrid based on solar-diesel-battery hybrid system. In MATEC Web of Conferences (Vol. 171, p. 01006). EDP Sciences.

Jayawardana, A., Fiorentini, M., Robinson, D. A., & Agalgaonkar, A. P. (2018). Economic Operation Optimisation of Battery Energy Storage Systems in a Solar Rich Microgrid.

Adhikari, U., Bhattarai, B. R., Karki, M., & Khan, S. (2019). Battery Energy Storage System Optimization for Grid-Connected Wind-PV Hybrid System. In Proceedings of the IOE Graduate Conference.

Ningzhou, X. (2011). Economic Operation Optimization for Microgrids Including Na/S Battery Storage.

Suciu, G., Badicu, A., Beceanu, C., Yümlü, M. S., Kaya, Y., Kızak, K. G., & Tahtasakal, F. (2021, March). AI-based intelligent energy storage using Li-ion batteries. In 2021 12th International Symposium on Advanced Topics in Electrical Engineering (ATEE) (pp. 1-5). IEEE.

Cordeiro-Costas, M., Villanueva, D., & Eguía-Oller, P. (2021). Optimization of the electrical demand of an existing building with storage management through machine learning techniques. Applied Sciences, 11(17), 7991.

Zidar, M., Georgilakis, P., Hatziargyriou, N., Capuder, T., & Škrlec, D. (2016). Review of energy storage allocation in power distribution networks: applications, methods and future research. Iet Generation Transmission & Distribution, 10(3), 645-652. https://doi.org/10.1049/iet-gtd.2015.0447

Ganesan, S., Subramaniam, U., Ghodke, A., Elavarasan, R., Kannadasan, R., & Bhaskar, M. (2020). Investigation on sizing of voltage source for a battery energy storage system in microgrid with renewable energy sources. Ieee Access, 8, 188861-188874. https://doi.org/10.1109/access.2020.3030729

Hameed, Z., Hashemi, S., Ipsen, H. H., & Træholt, C. (2021). A business-oriented approach for battery energy storage placement in power systems. Applied Energy, 298, 117186.

Ray, W. B., Subburaj, A. S., Schrock, J. A., & Bayne, S. B. (2015, October). Economic analysis of battery energy storage system. In 2015 IEEE Industry Applications Society Annual Meeting (pp. 1-7). IEEE.

Huu, D. N. (2021, February). A Quantitative Analysis of Battery Energy Storage System Integration Solutions into Isolated Hybrid Generation Networks: Application to Phu Quy Island. In 2021 11th International Conference on Power, Energy and Electrical Engineering (CPEEE) (pp. 56-63). IEEE.

Delfanti, M., Bovera, F., Falabretti, D., Merlo, M., & Rancilio, G. (2019). BESS located in Primary Substation for RES integration and ancillary services provision.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative research in psychology, 3(2), 77-101.

Hong, Q. N., Pluye, P., Fàbregues, S., Bartlett, G., Boardman, F., Cargo, M., ... & VEDEL, I. (2020). Mixed methods appraisal tool (MMAT) version française 2018. Education for Information.

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & PRISMA Group*, T. (2009). Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. Annals of internal medicine, 151(4), 264-269.

Popay, J., Roberts, H., Sowden, A., Petticrew, M., Arai, L., Rodgers, M., & Duffy, S. (2006). Guidance on the conduct of narrative synthesis in systematic reviews. A product from the ESRC methods programme Version, 1(1), b92.

Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence ‐ informed management knowledge by means of systematic review. British journal of management, 14(3), 207-222.

Appendices

Appendix 1. Python source codes for the cases

```
import numpy as np
import matplotlib.pyplot as plt
# Generate PV and load demand data
def generate_data():
    hours = np.arange(1, 25)
    pv_generation = np.maximum(0, 100 * np.exp(-((hours - 12)**2) / (2 * 3**2)))  # Bell-curve PV
    load_demand = 20 + 5 * np.sin((2 * np.pi * hours) / 24)
# Daily demand pattern
    return hours, pv_generation, load_demand

# Simulation function with charging enabled after discharging at SOC min
def simulate_case(case_name, pv_generation, load_demand, bess_capacity=100, bess_charge_rate=10):
    hours = np.arange(1, 25)

 # Initialize near-empty battery
    bess_soc = 5 if case_name == "Battery at SOC Min" else bess_capacity - 5
    bess_soc_list = []
    bess_power = []
    grid_power = []

    for pv, load in zip(pv_generation, load_demand):
        if case_name == "Battery at SOC Max":
            if bess_soc < bess_capacity:
                charge = min(pv - load if pv > load else 0, bess_capacity - bess_soc, bess_charge_rate)
                bess_soc += max(0, charge)
                bess_power.append(max(0, charge))
            else:
                bess_power.append(0)
            grid_power.append(0)

        elif case_name == "Battery at SOC Min":
            if pv >= load:
```

```
            # PV exceeds load: charge battery
            surplus = pv - load
            charge = min(surplus, bess_capacity - bess_soc, bess_charge_rate)
            bess_soc += charge
            bess_power.append(charge)
            grid_power.append(0)
        else:
            # PV < Load: try to discharge
            deficit = load - pv
            if bess_soc > 0:
                discharge = min(deficit, bess_soc, bess_charge_rate)
                bess_soc -= discharge
                bess_power.append(-discharge)
                grid_power.append(deficit - discharge)
            else:
                bess_power.append(0)
                grid_power.append(deficit)

        bess_soc_list.append(bess_soc)

    return hours, bess_power, grid_power, bess_soc_list

# Plotting function
def plot_case(case_name, hours, pv_generation, load_demand, bess_power, grid_power, bess_soc_list):
    plt.figure(figsize=(12, 6))
    plt.plot(hours, pv_generation, 'o-', label="RES (PV Generation)", color="blue")
    plt.plot(hours, load_demand, 'o-', label="Load Demand", color="red")
    plt.step(hours, bess_power, where='mid', label="BESS Power (Charge/Discharge)", color="green")
    plt.step(hours, grid_power, where='mid', label="Grid Power", color="orange")
    plt.xlabel("Hours [h]")
    plt.ylabel("Power [kW]")
    plt.title(f"Case: {case_name}")
    plt.legend()
    plt.grid()
    plt.show()
    plt.figure(figsize=(10, 5))
    plt.plot(hours, bess_soc_list, 'o-', label="BESS State of Charge (SOC)", color="purple")
```

```
    plt.xlabel("Hours [h]")
    plt.ylabel("SOC [kWh]")
    plt.title(f"BESS SOC over 24 Hours - {case_name}")
    plt.legend()
    plt.grid()
    plt.show()

# Run the two scenarios
hours, pv_generation, load_demand = generate_data()
for case in ["Battery at SOC Max", "Battery at SOC Min"]:
    hours, bess_power, grid_power, bess_soc_list = simulate_case(case, pv_generation, load_demand)
    plot_case(case, hours, pv_generation, load_demand, bess_power, grid_power, bess_soc_list)
```

Appendix 2. Python source codes for optimization

```
import numpy as np
import matplotlib.pyplot as plt

# Function to generate PV generation and load demand for 24 hours
def generate_data():
    hours = np.arange(1, 25)  # Time (1 to 24 hours)
    pv_generation = np.maximum(0, 100 * np.exp(-((hours - 12)**2) / (2 * 3**2)))  # Bell curve for PV
    #load_demand = 20 + 5 * np.sin((2 * np.pi * hours) / 24)  # Slightly variable load demand
    load_demand = 30 + 5 * np.sin((3 * np.pi * hours) / 24)
    return hours, pv_generation, load_demand

# Fuzzy Logic Controller
def fuzzy_logic_control(pv, load, soc, soc_min, soc_max, charge_rate):
    """Simulates real-time decision-making using fuzzy logic."""
    bess_power = 0
    if soc < soc_min:  # Low SOC: prioritize charging
        bess_power = min(pv - load, charge_rate) if pv > load else 0
    elif soc > soc_max:  # High SOC: stop charging or discharge
        bess_power = -(load - pv) if load > pv else 0
    elif pv > load:  # Excess PV: charge the BESS
        bess_power = min(pv - load, charge_rate)
    elif load > pv:  # Deficit: discharge the BESS
        bess_power = -min(load - pv, soc, charge_rate)
    return bess_power

# Model Predictive Control (MPC)
def mpc_control(pv_forecast, load_forecast, soc, soc_min, soc_max, charge_rate):
    """Simulates long-term planning using MPC."""
    bess_power = []
    soc_history = []
    for pv, load in zip(pv_forecast, load_forecast):
        if pv > load and soc < soc_max:  # Charge the BESS during excess PV
            charge = min(pv - load, charge_rate, soc_max - soc)
            bess_power.append(charge)
```

```
            soc += charge
        elif load > pv and soc > soc_min:  # Discharge the BESS during deficit
            discharge = min(load - pv, charge_rate, soc - soc_min)
            bess_power.append(-discharge)
            soc -= discharge
        else:  # Use the grid if BESS cannot meet demand
            bess_power.append(0)
        soc_history.append(soc)
    return bess_power, soc_history

# Function to simulate each case
def simulate_case(case_name, pv_generation, load_demand, bess_capacity=50, bess_initial_soc=25,
bess_charge_rate=10):
    hours = np.arange(1, 25)
    bess_soc = bess_initial_soc  # Initial SOC
    bess_soc_list = []  # To store SOC over time
    bess_power = []  # Power charged/discharged by the BESS
    grid_power = []  # Power drawn from the grid

    for pv, load in zip(pv_generation, load_demand):
        if case_name == "Fuzzy Logic":
            # Apply Fuzzy Logic control
            bess_action = fuzzy_logic_control(pv, load, bess_soc, soc_min=10, soc_max=bess_capacity,
charge_rate=bess_charge_rate)
            bess_soc += bess_action
            bess_power.append(bess_action)
            grid_power.append(max(0, load - pv - bess_action))  # Grid compensates any deficit

        elif case_name == "MPC":
            # Apply MPC control
            bess_power, bess_soc_list = mpc_control(
                pv_generation, load_demand, bess_soc, soc_min=10, soc_max=bess_capacity,
charge_rate=bess_charge_rate
            )
            return hours, bess_power, [max(0, load - pv - b) for b, pv, load in zip(bess_power, pv_generation,
load_demand)], bess_soc_list
```

```
        # Track SOC for other cases
        bess_soc_list.append(bess_soc)

    # Return results
    return hours, bess_power, grid_power, bess_soc_list

# Function to plot results
def plot_case(case_name, hours, pv_generation, load_demand, bess_power, grid_power, bess_soc_list):
    plt.figure(figsize=(12, 6))
    # Plot PV and Load
    plt.plot(hours, pv_generation, 'o-', label="RES (PV Generation)", color="blue")
    plt.plot(hours, load_demand, 'o-', label="Load Demand", color="red")
    # Plot BESS Power
    plt.step(hours, bess_power, where='mid', label="BESS Power (Charge/Discharge)", color="green")
    # Plot Grid Power
    plt.step(hours, grid_power, where='mid', label="Grid Power", color="orange")
    # Customize plot
    plt.xlabel("Hours [h]")
    plt.ylabel("Power [kW]")
    plt.title(f"Case: {case_name}")
    plt.legend()
    plt.grid()
    plt.show()

    # Plot BESS SOC
    plt.figure(figsize=(10, 5))
    plt.plot(hours, bess_soc_list, 'o-', label="BESS State of Charge (SOC)", color="purple")
    plt.xlabel("Hours [h]")
    plt.ylabel("SOC [kWh]")
    plt.title(f"BESS SOC over 24 Hours - {case_name}")
    plt.legend()
    plt.grid()
    plt.show()

# Main Program
if __name__ == "__main__":
    # Generate data
```

```
hours, pv_generation, load_demand = generate_data()

# Simulate and plot each case
cases = ["Fuzzy Logic", "MPC"]
for case in cases:
    print(f"Simulating case: {case}")
    hours, bess_power, grid_power, bess_soc_list = simulate_case(case, pv_generation, load_demand)
    plot_case(case, hours, pv_generation, load_demand, bess_power, grid_power, bess_soc_list)
```