# Energy Management System Strategies for Lithium-Ion Battery Storage: A Dual Approach for On-Grid and Off-Grid Systems

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***Abstract*—This study aims to explore the importance of Battery Energy Storage Systems (BESS) in the transition to renewable energy, particularly in supporting grid flexibility and standalone applications. It proposes an Energy Management System (EMS) based on using adaptive controls and predictive analysis to optimize the charging and discharging strategies of BESS, thereby improving system efficiency and economic viability. By dynamically monitoring environmental parameters and load demands, the EMS can adjust battery dispatch in real time to maximize the utilization of renewable energy and reduce peak power demand. The results indicate that BESS can effectively balance grid loads, reduce reliance on traditional peak power, and maintain system stability in both grid-connected and off-grid modes. Furthermore, this paper presents recommendations for improving technical, economic, and regulatory frameworks to facilitate the efficient integration of BESS with both grid and off-grid systems, as well as the deployment of renewable energy technologies.**

***Keywords*—Energy Management Systems (EMS), Photovoltaic (PV), Maximum Power Point Tracking (MPPT), Power conversion system, Automatic Transfer Switch (ATS), On-Grid, and Off-Grid**

## I. Introduction

The Paris Agreement aims to limit global temperature increases to well below 2°C, with the objective of achieving a temperature increase of 1.5°C or less compared to pre-industrial levels [1]. To meet these ambitious targets, a transformative shift towards renewable energy sources like solar and wind has emerged as essential alternatives to fossil fuels. To replace current fossil fuel usage, countries will require terawatt-hours (TWhs) [2] of electricity storage capacity. By 2030, current battery technologies are expected to be prioritized for the circular economy, with an estimated capacity of 4.7 TWh at a cost of $80/kWh [3]. The objective is to achieve zero emissions by 2050, with an estimated 10–13 TWh reaching 100% renewable energy use for cell production and recycling [4]. Contemporary BESS technologies are dominated by several types of batteries, including lithium-ion, lead-acid, sodium-sulfur, and emerging solutions like solid-state and flow batteries [5]. These systems key performance parameters—energy density, power density, cycle life, efficiency, safety and economical - determine their suitability for various applications, ranging from residential energy storage and uninterruptible power supplies to utility-scale operations in frequency regulation, reserve power, and demand response systems [6]. BESS reduces the need for expensive peaking power plants, lowers transmission and distribution costs, and improves the utilization of renewable energy. Modernizing the grid to integrate BESS involves hardware and software upgrades. Effective BESS design must mitigate degradation factors, enhancing battery lifespan and performance through advanced thermal management and smart algorithms. Moreover, the successful integration of BESS requires improved regulatory frameworks to clarify their roles and ensure fair compensation for ancillary services. EMS and BMS are at the heart of optimizing the performance and safety of BESS. It also provides the broader framework for integrating BESS with other grid resources, optimizing the dispatch of stored energy, and coordinating with renewable energy sources to maximize efficiency and reliability[7]. The EMS not only harmonizes the performance of these multiple units, but also ensures energy distribution is both efficient and responsive to real-time grid demands. In the context of predictive analytics and market integration, the EMS plays a vital role in facilitating data-driven decision-making and long-term planning. Whether in grid-on or grid-off applications, the functionality of the EMS becomes indispensable. It provides dynamic control and optimization, ensuring that BESS units can effectively respond to varying operational conditions and continue to supply reliable, high-quality energy. It empowers the grid to not only react to current conditions but also to anticipate future scenarios, thereby enhancing overall grid stability and economic efficiency.

## II. Literature Review

The integration of BESS enhances grid flexibility, enabling real-time response to fluctuations in demand and supply, and supporting grid services such as frequency regulation, voltage control, and load balancing, which are crucial for maintaining grid stability.

BESS involves different layers of systems and components involved in the integration and management with an electrical grid. Primary Scope: Focuses on the direct interaction and control between the battery, its management system, the inverter, and the grid. Secondary Scope: It Involves comprehensive energy management and supervisory control mechanisms overseeing multiple BESS units and their interaction with the grid. Tertiary Scope: Indicates higher-level integration and optimization, involving predictive analytics and forecasting to enhance grid operations and market interactions. This sophisticated control architecture is

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designed to facilitate energy flow, optimize battery usage, and enhance overall system performance [8]. When scaled up to a network of multiple BESS units, the necessity for an EMS becomes evident. The effective deployment and operation of BESS is contingent upon the functionality of the EMS [9].

Control System Optimization employs advanced EMS utilizing Real-time data analytics and machine learning algorithms to predict load demand and optimize battery dispatch [10], Blockchain technology to facilitate peer-to-peer energy trading [11], Leveraging predictive analytics on forecasts energy demand and adjusts the operation of individual battery systems [10], and weather forecasting and load analysis operation of battery storage systems depends on predicting solar generation and local load patterns [11]. Traditional EMS technologies manage battery systems by employing fixed profiles or real-time adjustments based on immediate data inputs. While these methods offer some level of efficiency, they often fall short in dynamically adapting to varying conditions and complex usage patterns. Fixed profile management involves pre-set charging and discharging routines that the EMS follows regardless of external conditions or battery state [12]. Although this approach simplifies the system design, it lacks the flexibility to adapt to changes in energy demands or to account for variations in renewable energy generation [13]. For instance, a fixed profile may not adequately respond to sudden surges in energy demand or prolonged periods of low renewable energy production, resulting in suboptimal battery utilization and potential efficiency losses. Not compatible to Large-scale systems, handle the complexity and variability of energy flows, absence of predictive analytics, ability to forecast energy demands and renewable energy generation results in result inefficient energy management practices, such as overcharging or discharging batteries at inopportune times, which can degrade battery health over time [14].

Real-Time Adjustments: More advanced than fixed profiles, real-time adjustment EMS strategies leverage immediate data inputs to make on-the-fly decisions regarding battery charging and discharging [15]. While this method allows for better responsiveness to changes in energy usage and generation, it often lacks the foresight to anticipate future conditions. Real-time adjustments can lead to reactive rather than proactive management, which might not always be optimal for maintaining battery health and system efficiency [16].

The regulation of electricity flow within the BESS is achieved through the implementation of intelligent algorithms that facilitate the optimization of charge and discharge cycles, the mitigation of thermal hotspots, and the assurance of balanced cell utilization, thereby extending the lifespan of the battery [17]. By continuously monitoring key parameters, such as the SoC, SoH, and temperature profiles, the EMS is able to identify potential failures and initiate corrective actions to avert catastrophic scenarios. The integration of predictive models and real-time analytics within the EMS framework enables the implementation of proactive maintenance strategies that enhance system reliability [18], in addition to technical performance, the economic viability of BESS is largely contingent upon the capabilities of the EMS. By optimizing energy scheduling and arbitrage, the EMS can facilitate the maximization of revenue streams from market participation, including energy trading, frequency regulation, and ancillary services.

Another crucial aspect is the seamless integration of BESS into existing grid frameworks, where the EMS plays a pivotal role. Ensuring interoperability and compliance with grid codes enhances market readiness and accelerates the adoption of BESS technologies [18]. To improve energy efficiency, reducing energy costs, and enhance the reliability of the system.

Energy Flow Management begins with distributing energy between on-grid and off-grid modes [19]. On-grid mode utilizes the power grid, while off-grid mode prioritizes local energy sources like solar and battery storage to enhance self-sufficiency. In off-grid mode, if energy becomes scarce, strategies such as load shedding are employed to disconnect non-essential loads and maintain stability [20].

The monitoring and fault detection process involves continuous observation of system parameters. This includes monitoring grid voltage for overvoltage and undervoltage protection and implementing anti-islanding detection to respond promptly to grid outages. Battery State of Charge (SoC) management ensures optimal battery performance and longevity, while thermal management regulates system temperatures. Fault detection identifies equipment malfunctions and initiates alerts for timely resolution [21].

The energy optimization process employs strategies to improve efficiency and cost-effectiveness, including peak shaving to reduce consumption during high demand and energy arbitrage to capitalize on price fluctuations. Maximum Power Point Tracking (MPPT) optimizes PV system performance, and charge/discharge optimization of batteries is based on real-time conditions. Load forecasting aids in planning and resource allocation by predicting future energy demand.

## III. Materials and Methods

Considering a Hybrid system, both On-grid and off-grid functionality as shown in Fig. 1. The ATS can switch to draw power from the grid and BESS when required.

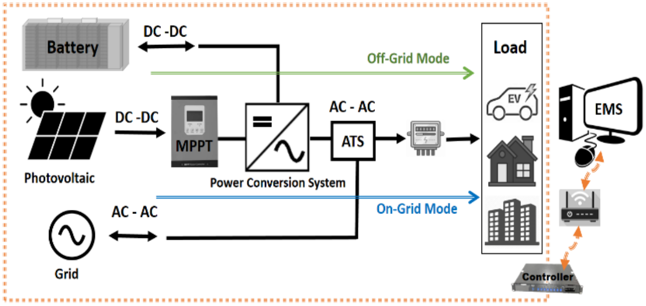


Fig. 1. Hybrid energy system integrating a battery, photovoltaic, and grid through a power conversion system, enabling both on-grid and off-grid modes, managed by an Energy Management System (EMS).

**On-Grid Mode,** the solar panels generate electricity, which is first directed to the loads. If the load demand exceeds the solar generation, the system draws power from the grid. Any excess solar power can charge the battery or be sent back to the grid, depending on the configuration and settings of the PCS, ATS and EMS.

**Off-Grid Mode,** the battery allows the system to supply power even when the grid is down or unavailable, making it operational in off-grid mode. When the grid goes down, the ATS switches to battery power, allowing the inverter to supply power to the loads from the stored energy in the battery. The solar panels can still provide power to the loads while charging the battery, depending on the battery's state of charge.

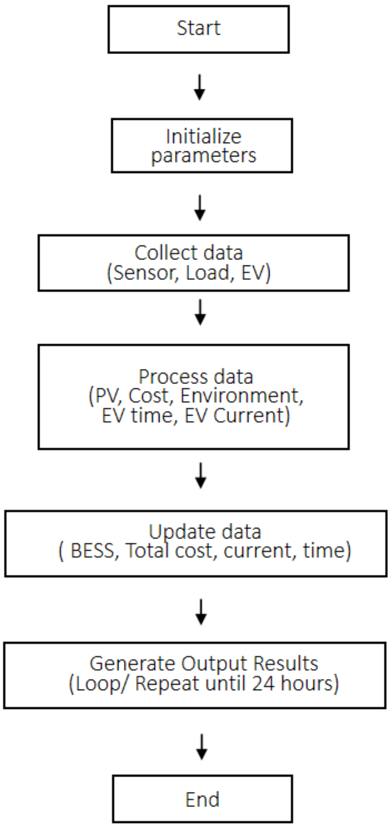


Fig. 2. Flowchart for Energy Management System (EMS) Data Processing and Result Generation.

The flowchart shown in Fig. 2. outlines the process of initializing parameters, collecting and processing data, updating system metrics, and generating output results in a loop for a 24-hour cycle in an EMS.

The parameters of the system are initialized, including charge rate, discharge rate, PV panel area, efficiency, and cell capacity including sensor data and load data. In the data processing and computing, the average values of environmental parameters and load are calculated, photovoltaic (PV) output is assessed, the status of the battery energy storage system is updated, the electric vehicle is charged while determining the total charging cost, and the current output alongside its associated costs is calculated.

Finally generating a comprehensive report that delineates the status of the system at each time interval, encompassing variables such as temperature, humidity, irradiance, load demand, as well as the charging and discharging currents.

System consideration, a battery system with a capacity of 200 kWh, with a usable energy is 160 kWh, the Photovoltaic Panel efficiency (η) 20% [22] and Average solar irradiance with 4 kWh/m²/day [23], EV Load (Tesla Model Y) [24]. Assuming temperature 25℃ with humidity of around 70%, a 24-hour electricity price is set and varies depending on the time of day as shown in Fig. 3. In this simulation work, we utilized parameters including Timestamp, Temperature, Humidity, Irradiance, Load Demand, Current Output, PV Output, BESS Energy Stored, EV Energy Consumed, Current Surplus, Current Deficit, Total Charge Cost, and Current Power Price.

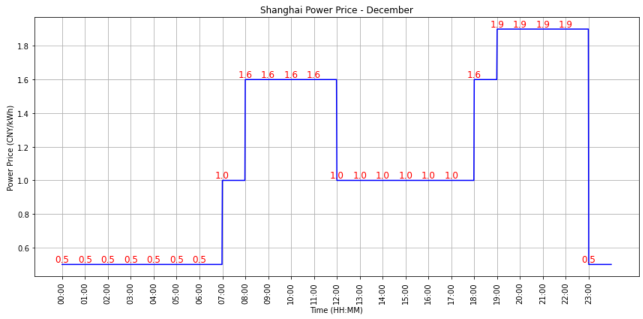


Fig. 3. The estimated hourly power price variation in Shanghai during December [25].

## IV. Result and Discussion

The algorithm employs an adaptive control system that dynamically modulates its parameters based on real-time data inputs. In the context of BESS, this enables the system to optimize its operational processes, and cost management, by assimilating information from incoming data streams. Adaptive control systems are inherently structured to autonomously adjust their operational behaviors. These parameters encompass nearly all initial conditions to enable a comprehensive prediction of the charge and discharge cycles of lithium-ion batteries, optimizing their response to fluctuations in demand and renewable energy supply. The system effectively determines when to charge the batteries (during periods of high solar output) and when to discharge them (during peak demand), ensuring grid stability by leveraging local demand forecasts and solar generation predictions to manage battery storage efficiently.

The load demand is constant and the PV output varies, the system likely relies on battery energy storage or grid connection to match the constant load demand during the periods when solar power is unavailable (before 10:00 and after 16:00), reaching a peak power of approx. 160 kW.

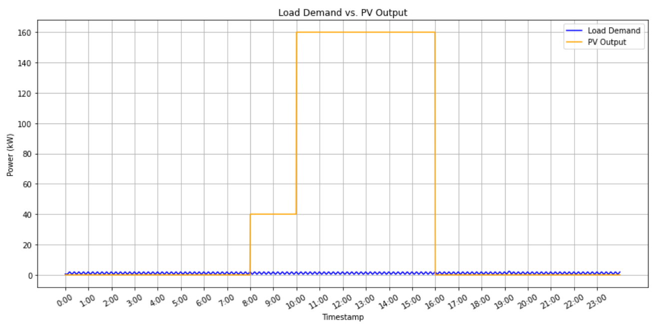


Fig. 4. Time series plot of load demand versus PV output.

Form Fig. 4, the peak load demand and the effectiveness of photovoltaic power generation can be observed. In an off-grid system, changes in load demand can directly affect the charging and discharging state of the battery. In a grid-connected system, photovoltaics can directly meet a portion of the load demand, with the remaining demand supplied through the grid. In a grid-connected system, the EMS can monitor grid price changes in real-time and charge when prices are low and discharge when they are high, maximizing economic benefits.

Fig. 5 indicates a roughly linear relationship between irradiance and PV output, where higher irradiance levels correspond to higher PV output. At 0 irradiance, there is 0 PV output; at around 1 $kW/m^2$, the PV output is approximately 40 kW. The maximum PV output is 160 kW at 4 $kW/m^2$ irradiance. This relationship is crucial for designing solar power systems, sizing energy storage, and assessing the overall effectiveness of the system for different geographical locations and weather conditions.

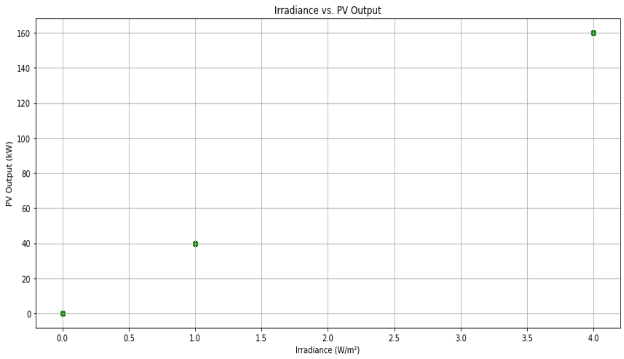


Fig. 5. Scatter plot of irradiance versus PV output.

In off-grid systems, changes in irradiance directly affect the power generation capacity of the PV system. By setting up a dynamic regulation mechanism, the EMS can increase the charging rate when the irradiance increases, ensure the maximum **utilization** of photovoltaic power generation. In grid-connected systems, combined with historical data and weather forecasts, the EMS can regulate the charging and discharging BESS scheduling pattern to develop competitive power quoting strategies.

The battery storage attains its full capacity of 200 kWh around 11:00 AM and maintains this level for the remainder of the day until the conclusion of the recorded period as indicated in Fig. 6. This observation suggests that the battery ceases to charge upon reaching its maximum storage capacity, as evidenced by the absence of further charging events subsequent to this point.

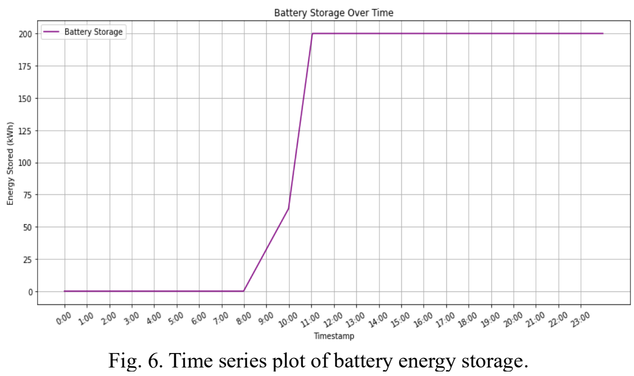


Fig. 6. Time series plot of battery energy storage.

The effectiveness of battery energy storage directly affects the reliability of the off-grid system as shown in Fig. 6. In a grid-connected system, the EMS can use battery storage to smooth out load fluctuations, ensuring a quick response during peak periods. By analyzing the changing trend of battery energy storage, the EMS can better carry out charge/discharge strategies to improve the economy and stability of the overall system. Furthermore, by interacting battery storage with the grid, the EMS can participate in the electricity market and leverage energy storage for arbitrage.

The surplus is observed only during day time from 9:00 AM to 4:00 PM when PV was charging, it can be seen from Fig. 7. The red lines at the bottom indicate periods of power deficit, while the tall green bars represent periods of power surplus, reaching up to approximately 150 kW between 11:00 AM and 4:00 PM. In off-grid systems, the EMS needs to effectively manage the charging and discharging process of batteries, ensuring timely storage when there is a surplus and fast power supply when there is a deficit. When there is a power deficit, the EMS should quickly activate backup power to ensure that load demand is met. In a grid-connected system, the EMS can sell excess electricity to the grid when there is a surplus, maximizing economic gains. In the event of a power deficit, the EMS should interact with the grid to balance supply and demand by regulating the load to ensure the stability of the system.

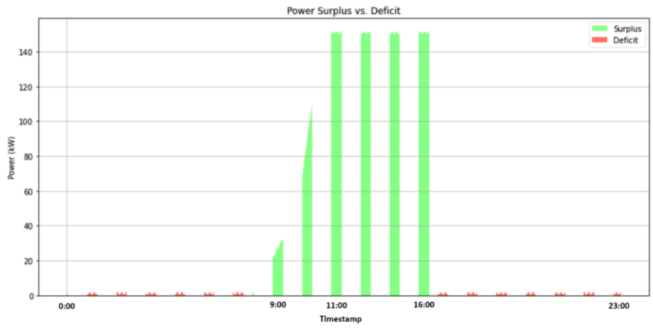


Fig. 7. Power surplus vs. deficit histogram (with selective time stamp).

Fig. 8. compares the energy consumed by Electric Vehicles (EVs) in kWh (blue line) and the total charging cost in currency units (orange line) over a one-hour period. EV charging occurs between 19:00 and 19:15, ranging from 2 to 6 kW, with a cumulative total of 42.93 kW, resulting in a straight line during this period. The cost gradually increases while EV energy consumption remains low. Energy consumption starts at 2000 units at 18:30 and rises linearly to 2200 units by 19:30. The inclusion of EV charging in the BESS system shows a negligible impact on the total load

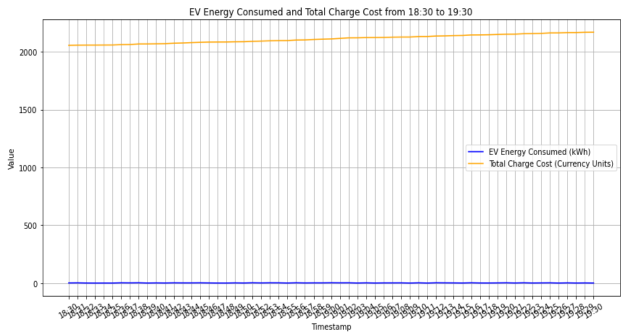


Fig. 8. EV Energy consumed and total charge cost from 18:30 to 19:30.

## V. Conclusion

This study highlights how effective EMS are in improving the flow of energy, ensuring reliability, and achieving economic benefits through the management of BESS. By using adaptive controls and predictive analysis, EMS can better align energy storage with solar power and demand variations, supporting grid stability and cost savings. The research confirms that BESS work well with photovoltaic systems, especially in off-grid areas, and help optimize energy usage in grid-connected settings by responding to market prices. Including electric vehicle charging in the BESS setup demonstrated a minimal impact on the overall system load shows its flexibility and capability to handle varied energy needs. Overall, integrating BESS into energy systems offers significant potential for sustainable energy and more adaptable grids. However, to realize these benefits fully, we need further improvements in EMS technology, regulations, and economic strategies to encourage broader adoption and optimization.

## Conflict of Interest

The authors declare no conflict of interest.

## Author Contributions

Zang was Responsible for the idea, gathering and summarizing relevant research on BESS; Yu focused on the setup and data requirements and operations; Singh wrote the code with the plots and results; Lyu integrated suggestions and prepared the final manuscript for submission; Dong checked all references for accuracy, ensuring that all citations followed the required style and format; all authors had approved the final version.

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