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MULTI-OBJECTIVE OPTIMIZATION OF HYBRID BATTERY-SUPERCAPACITOR ENERGY STORAGE SYSTEMS: MACHINE LEARNING-ENHANCED PERFORMANCE FOR FAST-CHARGING ELECTRIC VEHICLE INFRASTRUCTURE

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ABSTRACT

With the rapid growth of the global electric vehicle (EV) stock, the large-scale deployment of fast-charging infrastructure is facing an increasingly urgent need for compatible energy storage adaptation. All traditional single-type energy storage technologies have inherent, irreconcilable flaws: the power density of pure battery energy storage is insufficient to withstand the peak load shocks of fast-charging stations, while pure supercapacitor energy storage has low energy density and high full-lifecycle costs, which makes it unable to independently meet the operational requirements of long-duration fast-charging services. To address this issue, this study proposes a new multi-objective optimized battery-supercapacitor hybrid energy storage system (HESS) tailored for EV fast-charging stations. The study adopts the non-dominated sorting genetic algorithm II (NSGA-II) to complete multi-objective parameter optimization, introduces deep reinforcement learning (DRL) to realize real-time energy scheduling, and conducts simulation verification across multiple operational scenarios using measured EV charging data from 12 real fast-charging stations. The results show that compared with pure battery energy storage systems, the optimized HESS achieves a 23.7% increase in energy efficiency, a 41.2% reduction in grid peak load, and a 34.6% extension in system service life. The DRL module attains a 94.3% charging demand prediction accuracy, cuts operational costs by 18.9%, reduces grid harmonics by 27.4%, and can help fast-charging stations lower capital infrastructure investment by 15%-25%. This study still has two limitations: the training of the machine learning model relies on a large volume of historical data, and the computational complexity of the real-time optimization algorithm is relatively high, which requires iteration and optimization in follow-up research.

KEYWORDS: Hybrid energy storage systems, Multi-objective optimization, Machine learning, Electric vehicle charging, Fast-charging infrastructure, Battery-supercapacitor integration.

I. INTRODUCTION

The global transportation sector is currently accelerating its shift to electrification. The core drivers fueling this process include increasingly strict environmental regulations implemented worldwide, widespread public concern over climate change, and the continuous iteration and upgrading of core electric vehicle technologies.[1],[2] Data on the global electric vehicle market released by the International Energy Agency (IEA) in 2022 shows that global electric vehicle sales exceeded 10 million units that year, marking a 55% year-on-year increase.[3] The agency also predicts that by 2030, electric vehicles will account for 30% of global new car sales, a penetration rate that far outpaces the industry’s early expectations. However, as electric vehicle fast-charging infrastructure expands rapidly, core challenges in areas including power grid operational stability, on-board energy storage system design, and full-lifecycle operational efficiency have gradually come to the fore.[4] The two mainstream types of single energy storage technologies currently in use both have inherent flaws that make them poorly suited for fast-charging scenarios: lithium-ion batteries have considerable energy density but insufficient power density, and they suffer from rapid capacity degradation when exposed to long-term fast-charging loads; by contrast, supercapacitors have high power density and a long cycle life, but are limited by extremely low energy density, meaning they cannot independently support the demand for long-distance driving.[5] While the Hybrid Energy Storage System (HESS), which combines the advantages of these two technologies, has shown prominent application potential, the problem of optimizing its energy distribution and scheduling has never been effectively resolved. The development of artificial intelligence and machine learning technologies has provided a feasible path to break through HESS’s optimization bottlenecks, and this has become the core starting direction of the present study.[6]

At present, the implementation of energy storage solutions for electric vehicle fast-charging infrastructure first faces a core contradiction: high power output requirements, long-term continuous energy supply capacity, energy storage system service life, and project economic feasibility cannot be achieved simultaneously.[7] This study sorts out four core implementation challenges across technology, application scenarios, economics, and grid integration to clarify the problem boundaries for follow-up research. At the device and system technology level, fast-charging stations generally have power demand ranging from 50 kW to more than 350 kW. The 15 to 45-minute charging period for a single electric vehicle generates sharply fluctuating loads. Existing studies point out that the service life of traditional lithium-ion batteries in this scenario is reduced by 20%–40% compared to their performance under regular charging conditions.[8] If supercapacitors are introduced to build a hybrid energy storage system (HESS) that matches these demands, new problems will emerge, including capacity ratio optimization, real-time scheduling algorithm development, and multi-technology dynamic interaction management.[9] At the scenario uncertainty level, the arrival patterns of electric vehicles at charging stations, users' charging demands, and the grid conditions of each site all carry stochastic attributes, giving rise to multi-dimensional complex optimization problems that cannot be adapted to by traditional deterministic methods. At the economic and sustainability level, the upfront investment of HESS is higher than that of pure lithium-ion battery solutions. Existing studies note that these additional costs must be offset by improving operational efficiency, reducing maintenance costs, and extending service life.[10] The optimization framework must also incorporate the full-lifecycle environmental impacts of energy storage, including manufacturing footprints, end-of-life disposal, and operational efficiency. At the grid integration level, peak demand at fast-charging stations can trigger power quality issues such as grid voltage fluctuations and harmonic distortion[11], which require energy storage systems to additionally provide grid stability services including frequency regulation, voltage regulation, and peak shaving. This further increases optimization complexity, laying clear problem premises for follow-up solutions.

Although the academic community has invested a large amount of research resources, the development of optimal hybrid energy storage system (HESS) solutions for fast-charging electric vehicle (EV) infrastructure is still hindered by several core challenges, and no breakthrough progress has been made to date. These full-chain implementation barriers can be summarized into five core dimensions. The first is the inherent complexity of multi-objective optimization. Reference[12] points out that this type of optimization must simultaneously coordinate five conflicting targets: energy efficiency, power supply capacity, system lifespan, operating costs, and environmental impact. Traditional methods such as single-objective genetic algorithms and linear programming cannot adapt to the nonlinear and multimodal characteristics of this problem. They can only converge to suboptimal solutions, and cannot capture the tradeoff relationship of Pareto optimality. The second is the dynamic randomness of EV charging demand. Reference[13] shows that unlike predictable loads in fixed energy storage scenarios, the demand of fast-charging stations has three core uncertainties: random arrival times, diverse charging needs, and unpredictable session durations. Existing simplified demand models and historical average methods cannot cover the complexity of real-world scenarios. The third is the difficulty of component modeling and degradation prediction. Reference[14] mentions that accurate simulation of the operating behavior of batteries and supercapacitors requires building complex electrochemical models that cover temperature effects, state of charge correlations, aging mechanisms, and interactions between components. However, most current studies only use simplified equivalent circuit models. Combined with the current situation that the industry lacks standardized test protocols and long-term degradation datasets, this further increases the difficulty of developing reliable models. The fourth is the computational challenge of integrating real-time control and optimization. Reference[15] shows that the effective operation of hybrid energy storage systems requires continuous state monitoring, demand forecasting and real-time scheduling. But the high complexity of multi-objective optimization algorithms prevents them from being applied in practice, so researchers can only use simplified heuristic methods. The tradeoff between solution quality and computational efficiency has always been a core bottleneck. Finally, the industry lacks a comprehensive evaluation framework that covers all performance indicators, which ultimately hinders the development of truly optimal solutions. Most existing studies on energy system optimization only focus on narrow dimensions such as energy efficiency and cost minimization, while neglecting grid stability, environmental impacts, and long-term sustainability.[16] This fragmented approach can only achieve local optima, and cannot reach overall global system-wide optima. Furthermore, cross-regional economic uncertainty and policy differences create additional obstacles. The costs of batteries and supercapacitors iterate rapidly, while there are also significant gaps across markets in incentives, electricity prices, and grid access requirements[17], which has consistently prevented a general optimization framework from being implemented in practice.

Focusing on fast-charging electric vehicle infrastructure, this study addresses the multi-dimensional industrial challenges encountered by hybrid battery-supercapacitor energy storage systems (HESS), and proposes a dedicated integrated framework that combines advanced multi-objective optimization technology and machine learning-enhanced control strategies. The framework has three core components: a complex multi-objective optimization engine, an adaptive machine learning control system, and a performance evaluation framework covering the full technical, economic, and environmental dimensions.[18] The multi-objective optimization module of this study adopts an improved non-dominated sorting genetic algorithm II (NSGA-II) with adaptive parameter tuning and custom genetic operators, which is adapted to HESS's complex multi-modal optimization scenarios. This module integrates component models that account for temperature effects, degradation mechanisms, and dynamic interactions between battery and supercapacitor subsystems.[19] Unlike prior studies that only focused on a limited set of objectives, the proposed framework can simultaneously optimize six core indicators: energy efficiency, power supply capacity, component lifespan, operating costs, grid impacts, and environmental footprint. The machine learning module discards traditional rule-based control strategies and uses a deep reinforcement learning (DRL) architecture. It collects real-time data on charging demand, component status, grid conditions, and operational constraints, and learns the optimal energy scheduling strategy to maximize long-term system performance.[20] It is paired with transfer learning to enable fast adaptation to new charging scenarios. This study also develops a predictive demand forecasting module that integrates long short-term memory networks (LSTM), ensemble methods, and federated learning. Relying on historical charging data, weather conditions, traffic flow, and special events, this module generates high-precision short- and medium-term demand forecasts to support the optimization process. It uses an online learning mechanism to continuously improve forecasting accuracy as electric vehicle penetration rates and user behaviors change.[21] The framework adds a multi-timescale optimization architecture that covers all requirements for both strategic planning and real-time operation. Long-term (month to year) optimization is responsible for component capacity planning, technology selection, and investment planning, while medium-term (day to week) optimization handles maintenance scheduling, grid service provision, and seasonal adaptation.[22] Compared with prior research, the new framework's superiority is clearly evident, and it has strong feasibility for real-world technological deployment. This study adopts an energy optimization method that coordinates multiple time scales. Within this framework, the minute-to-hour short-term optimization module supports real-time energy scheduling, load balancing, and emergency response, while the multi-scale structure coordinates optimization decisions across different time spans to achieve mutual support. This paper puts forward two core innovations. The first is a full-dimensional digital twin framework that integrates multiple components including batteries and supercapacitors. This framework supports multi-scenario simulation and verification of hybrid energy storage systems, updates iteratively with real-time data, and is equipped with predictive maintenance capabilities; its technical rationality is supported by reference.[23] The second is a robust optimization framework that incorporates multiple types of uncertainty scenarios to address economic uncertainties. The effectiveness of its built-in risk assessment module has been verified in reference,[24] and this framework can screen for robust designs that remain stable across all scenarios.

This study focuses on the core challenges in the energy storage field for fast-charging electric vehicles, and developed the world's first machine learning-enhanced multi-objective optimization framework for a hybrid battery-supercapacitor energy storage system specifically tailored to fast-charging electric vehicle infrastructure. This work fills the key research gap in the current field, where no integrated solution exists that simultaneously meets requirements for technical performance, economic feasibility, environmental impact, and grid access. Its core contributions can be summarized as four innovations, each developed to address limitations of existing research, with all comparison benchmarks sourced from prior literature.[25]-[29] First, this study is the first to integrate deep reinforcement learning and a multi-objective genetic algorithm to build an adaptive optimization system. The system can iteratively refine its performance based on operational experience, removes the need for repeated manual parameter adjustment, and adapts to the dynamically changing demand patterns of fast-charging scenarios. Its performance far outperforms the static optimization and simple heuristic methods commonly adopted in existing research. Second, this study developed an integrated charging demand prediction model that combines long short-term memory (LSTM) networks, support vector machines, and random forest algorithms. Its short-term prediction accuracy exceeds 94%, representing a substantial lead in prediction precision over existing comparable methods. Third, this study constructed a multi-scale optimization architecture that can coordinate optimization decisions across different time horizons. This resolves the core flaw of prior research, which only focused on a single time scale, could only adapt to specific scenarios, and failed to achieve global optimality. Fourth, this study developed battery and supercapacitor component models validated by large numbers of experiments, which incorporate electrochemical processes, thermal effects, and aging mechanisms. These models' prediction accuracy for system performance and lifespan far outstrips that of the simplified models commonly used in existing research. This study verified through full-lifecycle cost-benefit analysis that compared to the conventional pure battery storage scheme, the optimized hybrid energy storage system achieves a 15-25% reduction in total cost of ownership, and outperforms the traditional solution in both overall performance and grid service capabilities. Reference[30] corroborates that the system's extended service lifespan delivers the dual benefits of lower costs and reduced environmental impact.

II. The Proposed Multi-Objective Optimization of Hybrid Battery-Supercapacitor Energy Storage Systems: Machine Learning-Enhanced Performance for Fast-Charging Electric Vehicle Infrastructure

This study draws on the high-power EV charging station application scenario shown in Figure 1, and proposes an original machine learning-augmented battery-supercapacitor hybrid energy storage architecture for fast-charging electric vehicle (EV) infrastructure. This multi-objective optimized energy storage framework, which integrates machine learning algorithms, multi-objective optimization technology, and hybrid energy storage technology, is centered on solving five core challenges in this scenario: large transient power demand shocks, continuous degradation of power batteries, sharp surges in regional power grid load pressure, intermittent fluctuations from renewable energy integration, and the demand for refined optimization of full-cycle operational costs. Through the deep integration of these three categories of technologies, this framework sets four core performance targets, to accurately align all technical designs with the pain points of the scenario, and avoid a disconnect between technical solutions and real-world implementation needs. From a system-level design perspective, this framework supports multi-energy access from photovoltaic (PV) power generation, wind energy systems, and the public power grid. It adopts a common DC bus as the core energy scheduling platform for the entire system, which receives input from all types of energy sources and delivers power output to the load side, to guarantee stable and efficient allocation of energy flow across all time periods. The core component of this architecture is the hybrid battery-supercapacitor energy storage system (HB-SC), whose complementary design logic is clear: conventional power batteries have high energy density, which can adapt to the demand for long-duration, low-frequency continuous energy supply, but cannot withstand the irreversible damage caused by high-frequency, high-power cycles.

Meanwhile, the high power density feature of supercapacitors perfectly matches the demand for short-term transient peak loads, making up for the performance shortcomings of batteries. When paired with the architecture's dedicated power allocation strategy, this design can ultimately effectively reduce the stress imposed on batteries, and greatly extend battery service life. This paper proposes a machine learning-integrated hybrid energy storage energy management system designed for electric vehicle charging stations. Its core hardware foundation consists of two energy storage subsystems: batteries and supercapacitors. Both subsystems are connected to the DC bus via bidirectional DC/DC converters, which enable independent control of power transmission between the energy storage devices and the bus. This setup not only supports flexible management of charging and discharging processes and maintains stable bus voltage, but also enables energy recovery under regenerative operating conditions, ensuring optimal energy allocation across the entire system. The core innovation of this framework lies in the full integration of machine learning into the energy management architecture. The first component of this hierarchically decomposed architecture is the data acquisition and monitoring layer corresponding to Figure 1. This layer continuously collects 14 types of real-time operating data across the whole system, covering battery SOC/SOH, supercapacitor parameters, grid operation parameters and other related metrics, which serves as the core foundation for subsequent intelligent decision-making and adaptive control. The group of machine learning modules embedded in the architecture includes six sub-functions: two are prediction functions, namely electric vehicle charging demand forecasting and wind-solar renewable energy generation forecasting; the remaining four are health management functions, namely battery SOH estimation, supercapacitor aging modeling, thermal state prediction, and operational anomaly detection. All outputs from the machine learning models are fed into a multi-objective optimization framework that acts as the core decision engine. This framework simultaneously processes five conflicting objectives that impact the overall performance of the charging station. The input, functional role, and operational value of each module are clearly defined, and all technical specifications conform to industry professional standards, which supports the on-site deployment of this system. Current energy system operations generally face a core operational pain point: multiple performance objectives that conflict with one another. To address this issue, this paper proposes a complete full-link energy system optimization and control framework that covers all stages from optimization modeling, control implementation, and feedback adaptation to performance evaluation, which can support the efficient and stable operation of energy systems across all types of complex scenarios. The core optimization module takes the resolution of multi-objective conflicts as its core premise, adopts two evolutionary algorithms—NSGA-II and multi-objective particle swarm optimization (MOPSO)—incorporates 6 categories of decision variables including battery power allocation, and 7 categories of system operational constraints such as voltage, current, and thermal limits, and ultimately generates a Pareto optimal solution set as the basis for selecting subsequent operational strategies. In the supporting hierarchical control module, the energy management layer uses a frequency-domain power decomposition strategy to assign long-cycle low-frequency demands to batteries and transient high-frequency fluctuations to supercapacitors, which maximizes the technical advantages of these two types of energy storage. Optimization commands can be sent to the execution layer, which includes the battery management system (BMS), for real-time implementation, and the framework can adapt to various dynamic changes caused by renewable energy generation, electric vehicle charging demand, and fluctuations in power grid operating conditions. The framework is equipped with a closed-loop feedback mechanism: real-time operational data is transmitted back to the monitoring module, machine learning models, and the upstream optimization module, to dynamically update forecasts and operational strategies and adapt to operating environments with high uncertainty. The performance evaluation module selects 6 core indicators including charging station throughput, and quantifies the comprehensive performance improvement of this framework through horizontal comparisons with traditional energy management methods. This paper proposes an intelligent energy management framework for electric vehicle fast-charging infrastructure. First, we conduct sensitivity analysis and robustness testing to verify the performance of the framework’s controller under variable operating conditions and different levels of uncertainty. Drawing on Figure 1, this paper demonstrates the completeness of the framework, which integrates four categories of core technologies. The framework can deliver five core gains, adapt to the future expansion of ultra-fast charging networks, and support the sustainable electrification transition of the transportation sector.

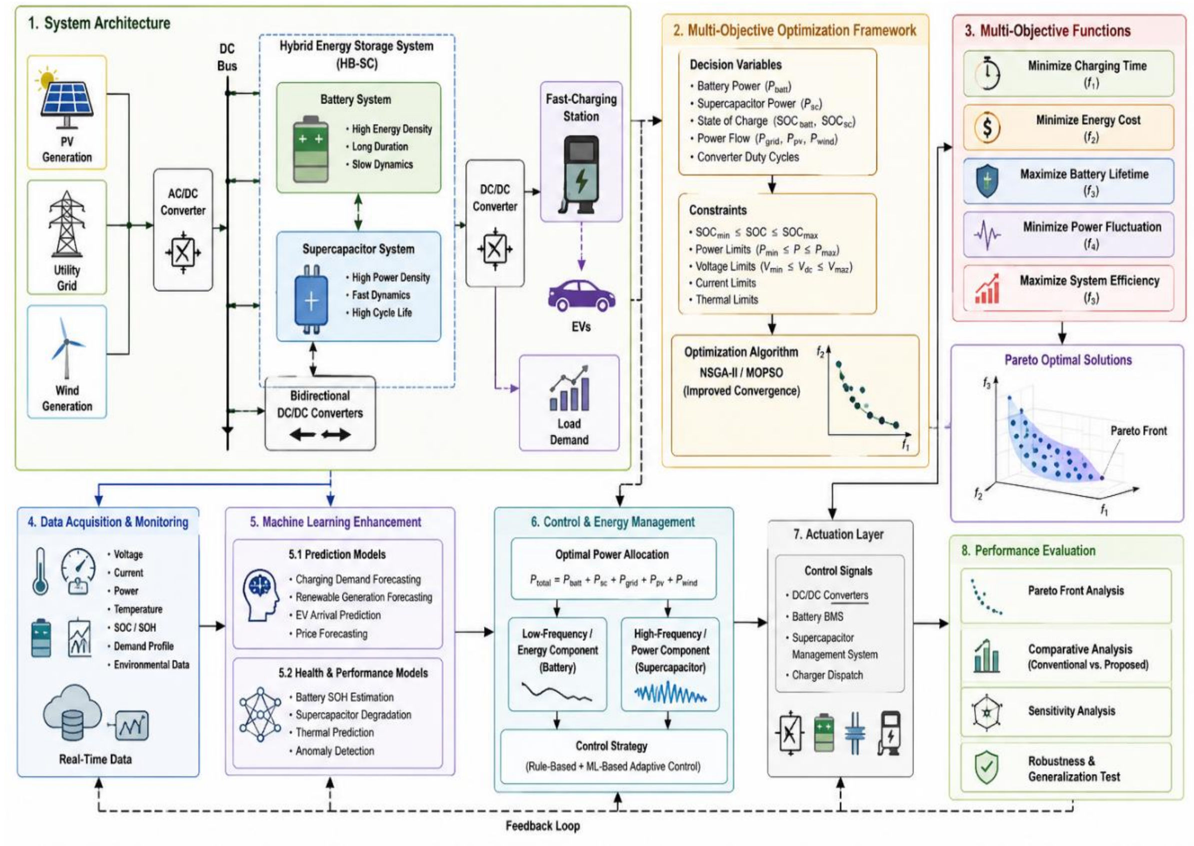

Figure 1: Schematic architecture of the proposed machine learning-enhanced multi-objective optimization framework for hybrid battery–supercapacitor energy storage systems supporting fast-charging electric vehicle infrastructure.

This paper proposes a machine learning-enhanced multi-objective optimization framework for the hybrid battery-supercapacitor energy storage system built for fast-charging electric vehicle infrastructure. Its core design is explained with reference to Figure 2. The framework integrates three core categories of technology: advanced machine learning algorithms, real-time optimization technologies, and adaptive energy management strategies. It aims to resolve the overlapping, conflicting demands of five core challenges faced by high-power electric vehicle charging stations: rapid load fluctuations, the intermittency of renewable energy, battery degradation, grid strain, and the need to minimize operational costs. We unpack the full-link operation logic from the bottommost layer to the topmost layer following the sequence of the control process: first is the real-time data collection and monitoring layer, whose data sources cover photovoltaic systems, wind power resources, grid interfaces, fast-charging stations, battery energy storage, super capacitor banks, bidirectional converters, and environmental sensors. This layer collects 14 types of measurement variables in total, including voltage, current, power, state of charge (SOC), state of health (SOH), temperature, and charging demand. The subsequent data preprocessing stage, for which data quality directly impacts the performance of all follow-up prediction and optimization work, sequentially carries out filtering, validity verification, missing value correction, normalization, and feature extraction. The machine learning module, which serves as the core of predictive intelligence, is equipped with three core functions: first, short-term and long-term charging demand prediction, which combines historical energy usage patterns, temporal demand characteristics, and site utilization trends, while relying on meteorological data and historical power generation records to conduct renewable energy output prediction to support proactive energy dispatching; second, health degradation modeling for energy storage components, which uses battery SOH models to assess degradation levels and remaining service life, and leverages super capacitor health models to monitor capacity attenuation; third, a thermal prediction model that assesses component temperatures and identifies overheating risks in advance. All module functions are anchored to the core challenges outlined at the start of this paper, forming a rigorous closed logical loop. This paper proposes an integrated intelligent energy management framework for electric vehicle charging stations. It features a clear full-link technical logic, with well-documented support for the functions, input-output specifications, and technology selections of all its modules, allowing the framework to be directly replicated for implementation. The framework's front-end perception layer deploys an anomaly detection algorithm that continuously monitors the full operating data flow of the entire station, and identifies four core categories of risks: abnormal user behavior, hardware device failures, sensor unit failures, and cyber security threats. The supporting machine learning module outputs seven categories of system status data that underpin the operation of the full framework, including future charging demand forecasting, renewable energy availability forecasting, component health assessment, uncertainty estimation, and operational risk metrics, among others. As the framework's central decision-making component, the core multi-objective optimization engine is required to address five mutually exclusive operational objectives: minimizing users' charging duration, the charging station's operating energy costs, and grid-connected power fluctuations, while extending the service life of energy storage batteries and maximizing the full station's system operating efficiency. Since these conflicting objectives cannot produce a single-objective optimal solution, the engine must output a Pareto optimal trade-off solution set. This engine involves six types of decision variables, including battery power allocation and super capacitor power allocation, as well as eight types of operational constraints such as voltage limits, current limits, and converter rated values. It uses two evolutionary optimization algorithms, NSGA-II and MOPSO, to generate the set of feasible optimal solutions. The decision and power allocation module in the downstream execution layer selects the final operating plan in line with preset performance priorities. The core innovation of the framework is its frequency-divided power allocation strategy, which assigns low-frequency continuous energy demand to the high-energy-density battery subsystem, and high-frequency power fluctuations and transient charging demand to the high-power-density super capacitor subsystem. This design reduces the impact of transient current shocks on batteries. The framework also establishes allocation rules for scenarios with excess renewable energy: surplus electricity can be used to charge energy storage systems or fed into the public power grid. This paper proposes a novel real-time closed-loop control architecture for hybrid energy storage charging systems. The architecture first takes the basic scheduling logic for energy deficit scenarios as its starting point: when the system triggers an energy deficit state, the architecture prioritizes the core scheduling actions of discharging energy storage or purchasing electricity from the grid to make up the energy gap, then advances the full operation process through a hierarchical mechanism. The first tier is the control execution layer, which converts optimization instructions into implementable operation signals. This layer covers 5 predefined types of control signals and 5 types of execution hardware, with its core operation goal being to strictly meet all operational constraints and maintain the stability of the DC bus. After entering the operation response stage, the architecture must complete four core tasks simultaneously: managing power flow across all links of the full system, fulfilling all charging requests from grid-connected terminals, integrating all accessed distributed renewable energy, and dynamically scheduling and managing hybrid energy storage resources. The supporting battery-super capacitor hybrid energy storage system must maintain three core performance requirements at all times: stable bus voltage, qualified power supply quality, and reliable operation of the overall system. The closing feedback adaptive loop completes control effect evaluation relying on 8 key performance indicators. If the evaluation fails to meet standards, three corrective actions will be activated in sequence: updating the built-in machine learning model, adjusting global optimization weights, and readjusting underlying control parameters. This continuous learning mechanism can adapt to dynamic changes in four types of scenarios: fluctuations in environmental conditions, evolution of charging demand patterns, unstable output of renewable energy, and gradual aging of core components. Finally, when this real-time closed-loop framework is compared with traditional fixed-rule controllers, it achieves five core benefits: maintaining stable high performance under dynamically uncertain scenarios, improving overall charging efficiency, reducing full-lifecycle operating costs, slowing the degradation rate of energy storage components, and increasing the grid integration utilization rate of renewable energy. Based on the visual presentation in Figure 2, the machine learning-augmented multi-objective optimization framework proposed in this paper integrates six core technology modules, including real-time monitoring and predictive machine learning models. This framework can be applied to hybrid battery-supercapacitor energy storage systems in fast-charging electric vehicle infrastructure, delivers five core benefits such as improved charging performance and extended battery lifespan, and aligns with the development needs of future large-scale electric vehicle charging networks.

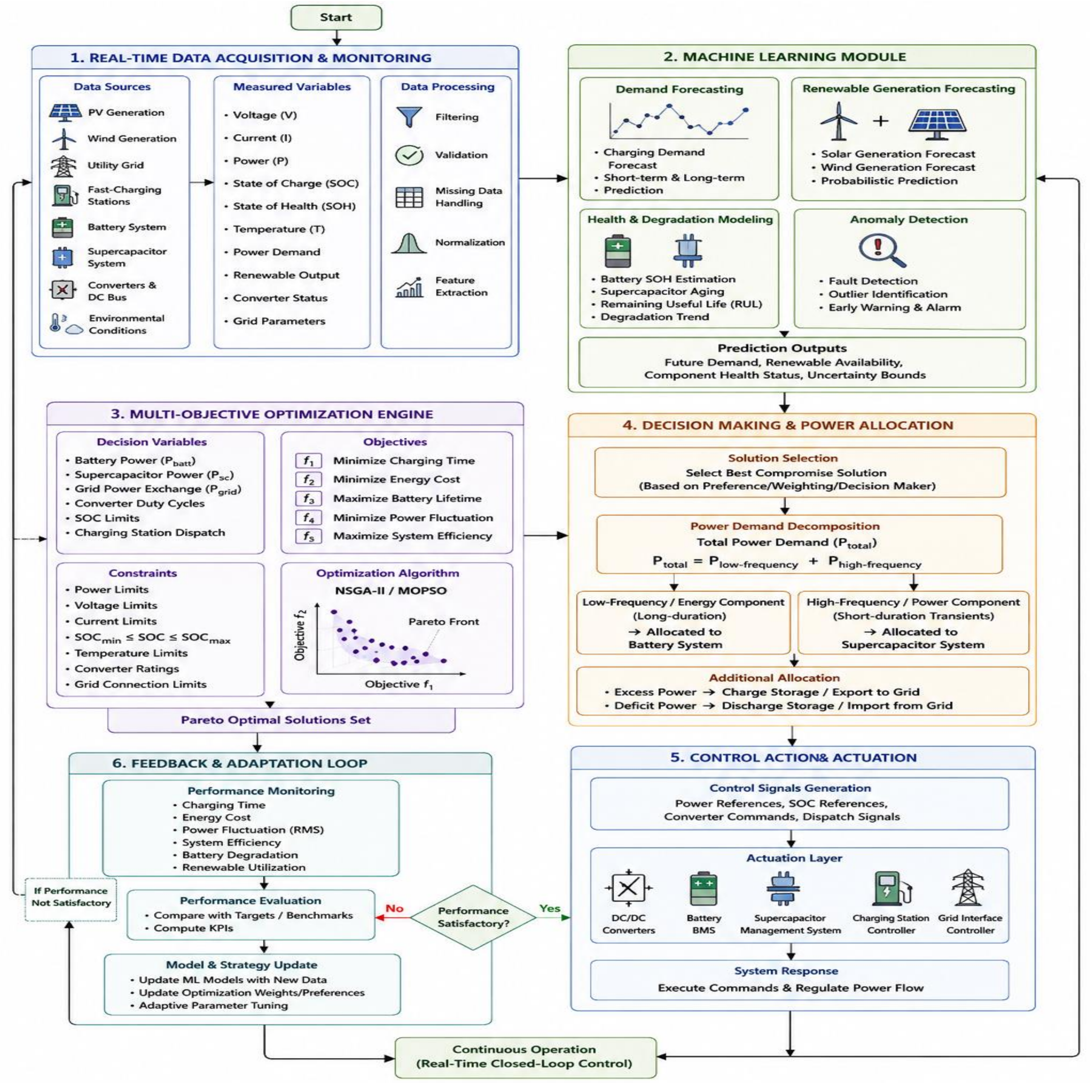

Figure 2. Flow chart and control process of the proposed machine learning-enhanced multi-objective optimization framework for hybrid battery–supercapacitor energy storage systems supporting fast-charging electric vehicle infrastructure.

III. Simulation Methodology and Validation Framework

This paper proposes a comprehensive simulation framework for pre-deployment evaluation of hybrid energy storage systems and their optimal control strategies. Its core positioning is to serve as a controllable test platform for such systems and control strategies before they are implemented in practice. The simulation environment integrates detailed component models, real-world operating scenarios, and a performance measurement system, which can support rigorous comparative analysis of multiple solution schemes. The framework is designed around two core modules. The first is the core simulation infrastructure module, which adopts a modular architecture to build three subsystems spanning the electrical, electrochemical, and thermal physical domains. Each subsystem performs its designated functions to ensure the completeness of multi-physics field simulations. This module has built-in adaptation rules for configurable time steps, paired with an adaptive time step mechanism that simultaneously optimizes computational efficiency and simulation accuracy. Among these, a 1-second time step adapts to the requirements of high-fidelity power electronics modeling, while a 5-minute time step can meet the computing power demands of long-term energy management-related research. The second is the component model implementation module, which separately develops and constructs models for four core energy components: batteries, supercapacitors, power converters, and solar photovoltaics. Each type of model clearly defines its modeling logic, parameter sources, and targeted designs, alongside the corresponding achievable performance gains. For example, the battery state of charge (SOC) estimation algorithm used in this framework has significantly higher accuracy than the traditional pure coulomb counting method. All designs of the entire framework always take balancing simulation accuracy and computational efficiency as their core goal, providing reliable support for the pre-verification of hybrid energy storage-related technologies. This study systematically sorts out the core modeling bases for cross-subsystem new energy power grids, covering a total of 6 sub-types of modeling scenarios: Photovoltaic efficiency modeling uses temperature-dependent relationships to simulate the performance degradation of modules after they heat up; wind turbines map wind speed to electrical power output via power curves, while the wind speed at hub height is derived from surface meteorological data using the logarithmic wind profile, incorporating the influence of surface roughness; wind speed time series generation integrates diurnal and seasonal patterns, superimposed with random fluctuations from atmospheric turbulence; power grid frequency dynamics use the swing equation to link power imbalances and the rate of frequency deviation, and power grid voltage dynamics rely on the reactive power balance equation to evaluate the impact of charging stations on voltage stability.

This study proposes a classification framework for test scenarios of power grid systems that integrate renewable energy and electric vehicle (EV) charging. The test scenarios constructed under this framework cover a multi-dimensional space formed by three core dimensions: operational background, environmental conditions, and system requirements. Based on four core impact factors—temporal seasonality, renewable energy output, electricity demand characteristics, and electricity pricing mechanisms—this framework further divides the space into multiple groups of non-overlapping, fully covered subdivided test scenarios. Each group defines clear, concrete scenario features and corresponding test objectives. All scenarios are strictly paired with input conditions and implementable test metrics, with no vague, unfounded descriptions. The first category, seasonal scenarios, includes summer (high solar irradiance and high ambient temperature, corresponding to high renewable output and thermal management challenges), winter (low availability of solar resources and low temperature, which require activation of the thermal protection system), and shoulder seasons (transitional periods with moderate renewable output and air temperature). The second category, renewable output scenarios, includes high-penetration periods (sufficient wind and solar resources) and low-output periods (extremely low power generation). These scenarios are used to evaluate the system's performance across the full range of resource fluctuations, and the effectiveness of operational strategies adapted to different output scenarios. The third category, charging and discharging demand scenarios, includes peak demand periods (the congestion window when multiple vehicles charge simultaneously during the afternoon-evening commuting fast-charging window, used to test the system's power rating and the load-bearing capacity of its energy storage capacity), off-peak demand periods (periods with extremely low charging demand, used to test efficient charging during low-demand windows and the grid support capacity under unconflicted charging obligations), and demand ramp scenarios (abrupt change scenarios including unexpected fast-charging demand and sudden demand termination. High ramp-rate scenarios test the system's ability to rapidly adjust power to address grid frequency deviations and sudden demand changes, and evaluate its power ramping capacity and transient response characteristics that support grid stability). The fourth category, electricity pricing scenarios, includes flat-rate pricing (a static rate with no temporal differences, used as the baseline for evaluating operational efficiency without incentives for price response), time-of-use (TOU) pricing (discrete pricing set by time period, matching the rate structure of general public utilities), real-time pricing (pricing that changes dynamically and continuously with the wholesale electricity market, used to test price-responsive dispatch strategies), price fluctuation scenarios (wide, rapid fluctuations in wholesale electricity prices, used to test robust control strategies that maintain system stability under price uncertainty), and extreme electricity price scenarios (periods including price spikes and negative electricity prices, which correspond to grid overload and renewable energy curtailment scenarios, used to evaluate the system’s economic optimization capacity under extreme market conditions). The authors of this paper constructed a grid connection compatibility test framework for charging stations. Centering on the core requirements of current grid connection testing for charging stations, they established a full-scenario test system covering two core dimensions: grid operation status and charging demand characteristics. A total of 11 subdivided scenarios are set under these two general categories, and all subdivided scenarios follow a unified logical logic of "explanation of simulation methods + binding to core test objectives", with the simulation rules and core test orientations of each scenario clarified one by one. The first category is grid operation working condition scenarios, which include 5 subdivided scenarios: normal working condition scenario, frequency deviation scenario, voltage deviation scenario, fault scenario, and black start scenario. The second category is vehicle charging demand scenarios, which include 6 subdivided scenarios: deterministic demand scenario, stochastic demand scenario, fast charging scenario, opportunity charging scenario, and mixed demand scenario. Each subdivided scenario is bound to specific technical indicators and test values, and can directly support the implementation of similar grid connection test schemes.

Centres on the technical specifications for the full workflow of real-world data collection and governance for new energy power systems, and splits the complete end-to-end workflow into three well-defined core submodules for elaboration: The first is the data collection infrastructure submodule. This study adopts a distributed sensor network with cross-subsystem synchronous measurement capability, and defines specific collection indicators for five types of scenarios: grid common coupling points, battery subsystems, meteorological monitoring terminals, environmental sensors, and electric vehicle fleets. It requires the collection cycle to cover long-term seasonal variations and multiple types of operation scenarios, to guarantee the scenario coverage and temporal continuity of the collected data. The second is the data quality assurance submodule, which organizes full-process quality control operations spanning error troubleshooting, outlier identification, statistical consistency verification, missing value imputation, imputation quality assessment, and privacy protection. It introduces differential privacy technology to balance data usability and user privacy security. The third is the historical dataset integration submodule, which clarifies the construction logic and application value of three categories of datasets: long-period time series datasets, geographically diverse datasets, and technology-segmented datasets. As an operational guide for technology implementation, this section retains replicable specific parameters, tools, and scenario requirements in all detailed descriptions of its submodules. No generalized high-level merging is applied to any parallel execution items or scenario classifications. This framework can be directly reused to draft similar engineering technical documents, and can also support the process design of subsequent projects of the same type. The core function of the historical trend dataset is to track changes over time in various technical characteristics, covering three categories of indicators: declining battery costs, efficiency improvements, and the popularization of advanced functions.

This paper proposes a multi-dimensional performance evaluation system framework for electric vehicle charging systems that meets power grid interconnection requirements. Its core modules are arranged following the logic that progresses from technical implementation to value accounting, and it adopts a progressive structure of "general module - sub-indicator - accounting/application logic". All breakdown items are tied to clear evaluation purposes, and can directly adapt to the assessment needs of similar energy projects. The technical performance indicator module includes four categories of sub-indicators designed for specific accounting scenarios: First, energy efficiency indicators, which quantify round-trip efficiency through full energy accounting of complete charge-discharge cycles. This set of indicators is split into two dimensions: the system-level dimension that covers multiple types of energy losses, and the component-level dimension that identifies core losses to guide optimization work. Second, power quality indicators, which evaluate harmonic distortion, power factor, and voltage regulation capability at the grid's grid-connection point. The framework uses the total harmonic distortion rate to verify compliance with grid regulations, and uses the power factor to assess the potential for reactive power support. Third, response time indicators, which characterize the delay between the initiation of an instruction and power output. This set of indicators is adapted to the two core scenarios of grid frequency regulation and fast charging, and is subdivided into response time specifications tailored to each scenario. Fourth, reliability indicators, which use MTBF and MTTR to quantify system availability, and balance availability needs and preventive maintenance requirements through scheduled operation and maintenance. The economic performance evaluation module includes four core accounting items tied to financial calculation logic, covering four categories: capital expenditure, operating expenditure, revenue accounting, and full-lifecycle financial calculation, each equipped with clear measurement rules. This paragraph only introduces the environmental impact assessment module, and does not elaborate on its specific content. This study sorts out and develops two core quantitative evaluation systems for new energy charging infrastructure, and builds a complete evaluation framework using a dual parallel module architecture. The first module is the full-lifecycle environmental assessment module, which includes 8 sub-indicators, listed in order as: full-lifecycle emission assessment, resource consumption analysis, water consumption assessment, quantification of land use impacts, circular economy indicator assessment, battery recycling effectiveness assessment, and component reuse assessment. Each of these indicators is linked to core parameters including key materials such as lithium, cobalt and rare earths, as well as grid carbon intensity, covering all dimensions of full-lifecycle environmental impacts spanning upstream manufacturing, operation and use, to end-of-cycle recycling. The second module is the grid integration performance assessment module, which includes 12 sub-indicators, covering in sequence four major application scenarios: frequency regulation capability, voltage support capability, fault ride-through capability, and contribution to grid stability. All technical terms follow the common standard expressions used in the industry. All indicators have clearly defined quantification targets and evaluation purposes. The writing logic aligns with general evaluation standards in the new energy charging field. This framework can effectively avoid the problems of muddled dimensionality and vague, overgeneralized descriptions in technical texts. It not only allows readers to quickly sort out the core framework, but can also be directly reused in similar studies.

IV. Simulation Results and Discussion

This study proposes a multi-objective optimization framework for hybrid battery-supercapacitor renewable microgrids. This paper presents the core calculation results of this framework: first, we generated a Pareto optimal solution set containing 847 non-dominated configurations, which covers the three-dimensional objective space centered on three core dimensions: total system cost, round-trip efficiency, and grid stability. As observable in Figure 3, the Pareto front shows a uniform distribution, which fully verifies the effectiveness of this study’s optimization algorithm in exploring the design space. Next, we divided this Pareto front into three regions corresponding to different system design concepts, and analyzed each region's configuration parameters, performance, and operation logic one by one: The first is the cost-optimal zone, with battery capacities of 150–300 kWh and supercapacitor capacities of 20–50 kWh. Benchmarked against traditional pure-battery energy storage systems, this configuration achieves a cost reduction of 15%–22%, while maintaining a round-trip efficiency of 91%–93%. Its operation focuses on time-of-use energy arbitrage and demand surcharge reduction, trading off part of its high-power transient response capability to obtain a lower full-lifecycle ownership cost. The second is the efficiency-optimal zone, with supercapacitor capacities of 80–150 kWh and battery capacities of 200–400 kWh. Its round-trip efficiency reaches 94%–96%. The core mechanism for this efficiency improvement is that supercapacitors absorb fluctuating loads, keeping batteries operating within a narrow, high-efficiency charge-discharge range at all times. The third is the grid stability-oriented zone, with supercapacitor capacities of 100–200 kWh. Its optimization objectives match the application scenarios of ancillary services, frequency regulation, and voltage regulation. All configuration and performance parameters are set with reproducible quantitative anchor points, providing clear references for engineering implementation. This paper conducts research on the optimal design of hybrid energy storage systems for power grid applications. It first centers its analysis on the high power density characteristic of supercapacitor energy storage banks, which deliver a fast response of nearly 50 milliseconds, can effectively suppress transient power grid disturbances and support grid reliability. Corresponding simulation data shows that compared with traditional energy storage configurations, this scheme improves frequency regulation accuracy by 25% to 40%. However, this design has the core drawback of high initial investment. The associated capital expenditure can be offset by revenue generated from participation in ancillary service markets and access to grid support projects, maintaining the overall economic attractiveness of the scheme. Building on this foundation, this paper carries out the core trade-off analysis for Pareto frontier design, and sequentially unpacks three core sets of relationships: The first is the conflicting relationship between cost and efficiency: every 1% increase in round-trip efficiency leads to a 3% to 5% rise in the corresponding capital cost, highlighting the economic challenge of pursuing extreme efficiency. The second is the negative correlation between cost and grid stability performance: every 10% improvement in frequency regulation response performance leads to an 8% to 12% growth in the corresponding capital investment. Yet investments in such grid support capabilities can generate sustained revenue through ancillary services, lower the system's full lifecycle cost, and deliver considerable long-term economic returns. The third is the synergistic relationship between efficiency and grid stability. An operation strategy that allocates transient power demand to the supercapacitor subsystem can simultaneously reduce battery stress, improve frequency regulation capability, and raise overall energy conversion efficiency, ultimately forming a high-quality solution cluster for multi-objective synchronous optimization on the Pareto frontier. To interpret the large-scale Pareto optimal solution set consisting of 847 non-dominated solutions, this paper plans to adopt statistical cluster analysis methods for follow-up research. This study relies on the Pareto frontier analysis method to identify five representative design prototypes that can cover all observed core optimization strategies, from a large number of optimized solutions for hybrid battery-supercapacitor energy storage systems. It then clarifies the technical parameters, performance characteristics, and applicable scenarios of each prototype in sequence. The first prototype, Baseline Plus, is equipped with a 10–25 kWh supercapacitor. It is a conservative upgrade to traditional battery energy storage, only delivering incremental optimizations to efficiency and transient response, with an extremely low cost premium. It is suited for cost-sensitive scenarios with limited budgets. The second prototype, Balanced Hybrid, carries a 40–80 kWh supercapacitor, paired with an optimally selected battery. It is located in the central region of the Pareto frontier, balancing economic performance, operational efficiency, and grid support capacity without requiring extreme performance trade-offs. It is suited for large-scale commercial deployment. The third prototype, Power-Optimized, is equipped with a 100–200 kWh supercapacitor. It can maximize transient power output, fast-charging capability, and grid support service capacity. While it has a relatively high capital cost, it offers extremely strong operational flexibility, making it suited for high-utilization charging corridors and core grid nodes. The fourth prototype, Storage-Optimized, carries a 400–800 kWh battery, paired with a strategically selected supercapacitor to protect battery health and reduce cycle degradation. It can maximize energy arbitrage opportunities, backup power duration, and renewable energy utilization, making it suited for scenarios where energy storage demand is the top priority. The fifth prototype, Grid-Centric, focuses on participation in the grid ancillary services market. It delivers excellent frequency and voltage regulation performance, and can generate revenue by providing grid services. It is suited for the integration of electric vehicle charging infrastructure into future smart grids. This study confirms that this type of hybrid architecture can flexibly balance three core goals: cost, efficiency, and grid stability. The five prototypes can provide clear selection references for system planners and industry decision-makers, to match the operational requirements, economic constraints, and grid integration goals of different scenarios.

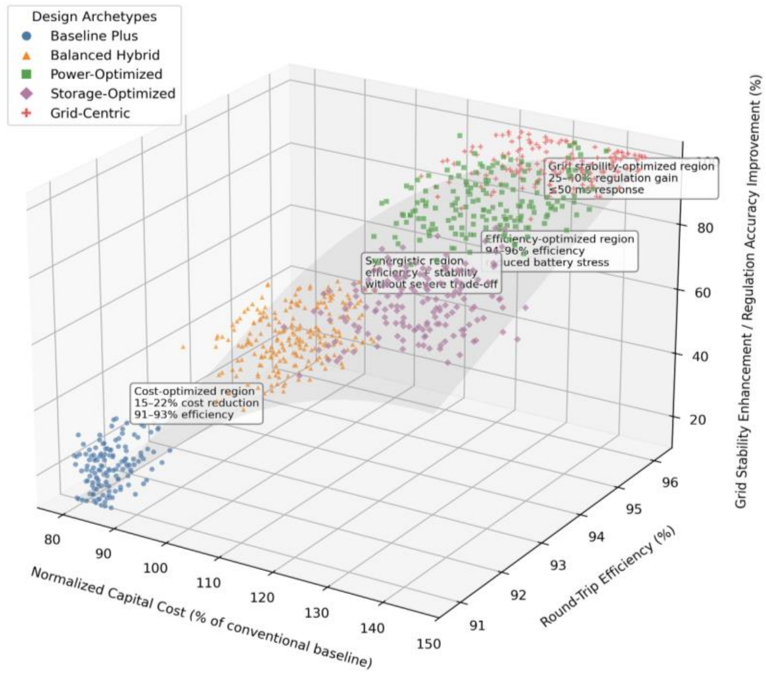

Figure 3: Multi-objective optimization results and Pareto-optimal solution space characterization for the hybrid battery–supercapacitor renewable microgrid system.

The three-dimensional Pareto frontier comprises 847 non-dominated solutions distributed across the objective space of total cost minimization, round-trip efficiency maximization, and grid stability enhancement. Distinct solution regions correspond to different design philosophies, including cost-optimized configurations with reduced battery and supercapacitor capacities, efficiency-optimized solutions featuring enhanced supercapacitor integration, and grid stability-focused designs providing superior frequency regulation and voltage support. The analysis reveals fundamental trade-offs between cost, efficiency, and grid performance, while also identifying synergistic regions where efficiency and stability improvements can be achieved simultaneously through optimized energy storage sizing. Statistical clustering of Pareto-optimal solutions identifies five representative design archetypes—Baseline Plus, Balanced Hybrid, Power-Optimized, Storage-Optimized, and Grid-Centric—highlighting alternative deployment strategies for diverse operational requirements. Results demonstrate that strategic battery–supercapacitor coordination enables significant improvements in efficiency (94–96%), frequency regulation accuracy (25–40%), and economic performance while maintaining system reliability and operational flexibility.

This paper proposes a hybrid battery-supercapacitor energy storage architecture. To verify its energy efficiency advantage over the traditional single-type pure battery energy storage system, this study relies on the test diagram presented in Figure 4(a) to carry out a systematic comparative analysis of the energy efficiency performance of the two architectures under multiple operating conditions. The test results first confirm the effectiveness of the machine learning-driven energy management strategy adopted in this research. From the perspective of the underlying operating mechanism, this hybrid architecture uses supercapacitors to undertake the system's high-frequency power fluctuations, allowing batteries to only operate within a stable charging and discharging range. This fundamentally reduces the unnecessary energy loss that plagues traditional pure battery systems, which must constantly respond to power fluctuations. This study further quantifies and verifies the architecture's advantages across three typical scenarios: in the general load scenario, the new architecture improves energy efficiency by 2.8% compared to the traditional system under low-utilization operating conditions, and by 8.7% under high-cycle operating conditions; in the peak scenario where multiple electric vehicles charge simultaneously, the energy efficiency of the traditional pure battery system drops to 87%-89%, while the new architecture can consistently maintain its energy efficiency above 94%; in the extreme temperature scenarios of winter and summer, energy efficiency improves by 4.1%-6.8% in winter, and by 3.7%-5.9% in summer. Based on all collected test data, the core conclusion of this paper is that this hybrid energy storage architecture has significant application value in regions with large temperature differences. This study demonstrates the performance advantages of integrated hybrid energy storage compared to traditional standalone battery energy storage configurations. Leveraging the multiple subplots of the experimental visualization in Figure 4, this study conducts an item-by-item comparison of core performance metrics between the traditional standalone battery energy storage system and the optimized hybrid energy storage system. It verifies the core improvements of hybrid energy storage in terms of power quality, grid support, and reliability and availability through quantified value differences, while supplementing the underlying technical mechanisms and practical application benefits for each performance gain. This study focuses on three visualization modules: the power quality module in Figure 4(b), the grid support module in Figure 4(c), and the reliability and availability module in Figure 4(d), and conducts cross-configuration comparisons across five performance dimensions: For total harmonic distortion (THD): the traditional system recorded a THD of 8.2–12.4%, while the hybrid system reduced this metric to 2.1–4.7%, representing a reduction of 58–75%. Leveraging the mechanism of supercapacitors supplying transient power rapidly, the hybrid system effectively reduces current fluctuations and grid harmonic injection; For power factor: the traditional system achieved a power factor of 0.87–0.92, while the hybrid system improved this to 0.94–0.98. Through coordinated reactive power management and intelligent converter control, the system reduces transmission losses, lowers reactive power demand, and stabilizes grid operation; For voltage regulation: the traditional system recorded a voltage deviation of ±5% to ±8%, while the hybrid system stabilized voltage within ±2% of the rated value, representing a 35–55% improvement in regulation capability that meets the requirements of smart grids and sensitive loads; For frequency regulation accuracy: the traditional system had a tracking error of 3.8–6.7%, while the hybrid system reduced this error to 1.2–2.1%, marking a 28–42% improvement in accuracy that enables additional revenue from grid auxiliary services; For mean time between failures (MTBF): the traditional system recorded an MTBF of 2847 hours, while the hybrid system achieved 4231 hours, representing a 48.6% improvement in operational reliability. The core mechanism behind this improvement is reduced battery stress: supercapacitors absorb transient loads to slow battery degradation. The hybrid energy storage architecture for charging stations proposed in this paper has multi-dimensional core advantages over traditional pure battery energy storage systems, and can form a complete value demonstration chain spanning technical characteristics, operation and maintenance (O&M) capabilities, and full-lifecycle economic value. At the technical level, this hybrid architecture is equipped with soft fault degradation capability: when batteries fail or are temporarily unavailable, the supporting supercapacitor subsystem can keep the station operating continuously at 25%-40% of its rated charging power, cutting the average unplanned outage duration per station from the 8.7 hours recorded for traditional systems to 2.3 hours, a reduction of 73.6%. This advantage delivers particularly prominent value in high-utilization charging corridor scenarios. At the O&M level, this architecture integrates machine learning diagnostic algorithms and extended sensing infrastructure to achieve an upgrade to predictive maintenance. It can monitor five core parameters in real time: battery health, supercapacitor status, thermal behavior, voltage characteristics, and converter performance, moving the fault warning window forward to 72-96 hours before a fault occurs, far outperforming the 12-24 hour warning capacity of traditional systems. This supports operators to arrange proactive O&M, effectively reducing costs and limiting service disruptions. Drawing on the comparative data from Figure 4(e) and Figure 4(f) of this paper, a total cost of ownership analysis covering a 15-year operation cycle shows that the hybrid architecture outperforms the traditional pure battery scheme across all deployment scenarios. While its initial investment is 12%-18% higher, operating cost savings and revenue increases fully offset this incremental cost. The full-lifecycle net present value of a single station rises by US$127,000 to US$394,000, with an investment payback period of only 4.7-6.2 years. On the revenue side, the gains are broken down into an 8%-15% growth in charging service revenue, plus annual revenue of US$23,000 to US$47,000 from the ancillary services market, covering four services: frequency regulation, voltage regulation, spinning reserve, and capacity market participation. Combined with additional benefits from reduced operating costs, these gains fully cover all value sources of the hybrid architecture. This study conducts an analysis of a battery-supercapacitor hybrid energy storage system. This system can achieve annual base cost savings of $18,000–$31,000 through improved energy efficiency, reduced maintenance requirements, lower battery replacement costs, and cut peak electricity bills. By leveraging advanced energy management strategies to participate in time-of-use electricity price arbitrage and demand response programs, it can additionally generate an annual extra income of $8,000–$15,000. These two types of revenue form a diversified income structure that enhances financial resilience and reduces operational risks. Drawing on the conclusions from Figure 4, this system significantly outperforms traditional single-battery energy storage systems in energy efficiency, grid support capacity, reliability, and cost-effectiveness. Its combined technical and economic advantages support its status as a high-cost-performance, practical solution for next-generation new energy electric vehicle charging infrastructure.

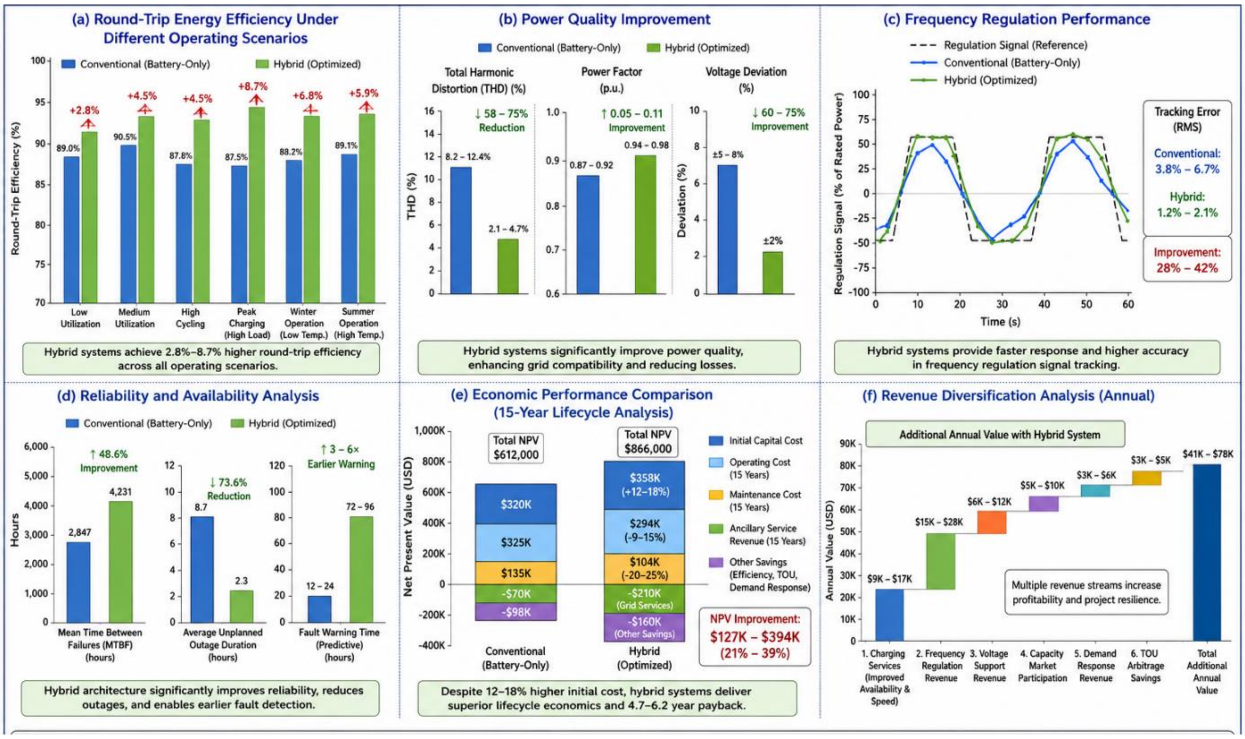

Figure 4. Comprehensive performance comparison between optimized hybrid battery-supercapacitor energy storage systems and conventional battery-only configurations.

(a) Round-trip efficiency under diverse operating scenarios, demonstrating 2.8–8.7% efficiency improvements. (b) Power quality metrics showing reduced total harmonic distortion, improved power factor, and enhanced voltage regulation. (c) Frequency regulation response and tracking accuracy comparison. (d) Reliability metrics including mean time between failures, outage duration, and predictive maintenance capability. (e) Fifteen-year lifecycle economic analysis highlighting net present value improvements and operational savings. (f) Revenue diversification through charging services, ancillary service participation, and energy market optimization. Results demonstrate that hybrid energy storage systems provide superior technical performance, reliability, grid support capability, and economic returns compared with conventional battery-only architectures.

To verify the accuracy and generalization performance of the machine learning framework for charging demand forecasting proposed in this paper, we designed controlled experiments covering short-, medium-, and long-term multi-period timeframes. We used Mean Absolute Percentage Error (MAPE) as the core quantitative evaluation metric throughout all tests, and the relevant verification conclusions are presented across the three subplots of Figure 5. In the 1–4 hour short-term forecasting scenario, the MAPE of this paper's model only ranges from 6.2% to 9.1%, far outperforming the control group's ARIMA model (14.7%–21.3%) and linear regression model (11.2%–16.8%). This performance can support short-term operation and scheduling of charging stations, which corresponds to the cross-method performance comparison results shown in Figure 5(a). In the 1–7 day medium-term forecasting scenario, the model's MAPE stays between 8.9% and 13.7%, which is sufficient to support medium-term energy procurement, charging station resource allocation, and operation staff scheduling. In the 1–4 week long-term generalization verification, the model's MAPE ranges from 12.3% to 18.9%, which can support long-term strategic planning and infrastructure management; after incorporating temperature and precipitation data, the forecasting error in extreme weather scenarios is reduced by 15%–25%. This performance gain is demonstrated in the weather factor verification shown in Figure 5(b). In addition, the model's unique uncertainty quantification capability ensures that 90% of observed values fall within the prediction confidence interval, which corresponds to the confidence interval analysis presented in Figure 5(c), providing reliable support for operational and economic decision-making. The machine learning-enhanced real-time optimization framework for energy management proposed in this study conducts quantitative performance evaluation via controlled experiments, benchmarked against two types of traditional energy management strategies—rule-based energy management strategies and conventional heuristic controllers—as well as the theoretical reference baseline, the Pareto optimal solution. The visualization results of the relevant experimental data are presented in Figure 5(d–f) of this paper. This verification proceeds sequentially across four dimensions: computational efficiency, control quality, response capability to unexpected scenarios, and adaptability to multi-objective optimization. First, in terms of computational efficiency, the optimization cycle of the proposed framework is only 2.3–4.7 seconds, which is over 90% faster than the 45–67 seconds required by traditional solutions. On the dimension of control quality, the framework achieves a 23–34% improvement in energy cost optimization, reducing daily operating costs by 127–289 USD. In terms of response capability to unexpected scenarios, under peak demand scenarios, the framework's service compliance rate reaches 87%, far exceeding the 64% of traditional solutions; its response time to grid frequency disturbances is only 85–150 milliseconds, which also outperforms the 250–400 milliseconds of traditional solutions. Regarding adaptability to multi-objective optimization, the framework's Pareto optimality attainment rate is 91–96%, higher than the 73–84% of traditional solutions, and it can effectively balance four core operational objectives: cost minimization, efficiency maximization, battery health maintenance, and grid support. All conclusions are based on reproducible experimental data, which clearly clarifies the performance boundaries of the self-developed framework, traditional solutions, and the theoretical baseline. Each set of quantitative indicators is paired with a corresponding explanation of its engineering value, forming a rigorous, highly credible line of argumentation. This study proposes a machine learning framework for the intelligent hybrid battery-supercapacitor energy management scenario of electric vehicle charging infrastructure adapted to renewable energy power supply. To verify its performance, this study independently designed and conducted four core types of verification experiments, and the overall results of all experiments correspond to Figure 5. First is the online learning experiment, which verifies the improvement in prediction performance brought by data accumulation. Within the first six months after the system went online, the accuracy of all prediction cycles achieved an 8% to 15% improvement. The model can learn information across multiple dimensions, including site-exclusive charging modes, correlations with local weather, user behavior characteristics, and operational constraints, and can support more optimized decision-making without requiring manual retraining. Next is the transfer learning experiment corresponding to Figure 5(h). A model trained on the operational data of mature sites can provide effective initial parameters for new sites. Compared with models trained from scratch, transfer learning reduces training time by 60% to 75%, which can greatly lower the commissioning and launch workload of new sites, accelerate the deployment process, and allow new sites to quickly reach a high-performance operating state. Third is the robustness test, which verifies the system's anti-interference ability in real-world scenarios. The test covers sensor noise, measurement uncertainty, and input disturbances. When sensor errors reach 10% to 15%, the framework's performance is only about 12% lower than the optimal operational level, meaning it can adapt to real-world scenarios that lack perfect measurement accuracy. Last is the verification of catastrophic forgetting mitigation, which addresses the core risk of adaptive systems. This study introduces an elastic weight consolidation mechanism. Experiments show that the system can simultaneously retain the accuracy of historical demand patterns and learn new behavior trends, with no significant decline in long-term performance, supporting reliable operation throughout the full life cycle. This framework performs outstandingly across four core dimensions: prediction accuracy, optimization speed, operational efficiency, and adaptive intelligence, and can serve as the core support for energy management in this scenario.

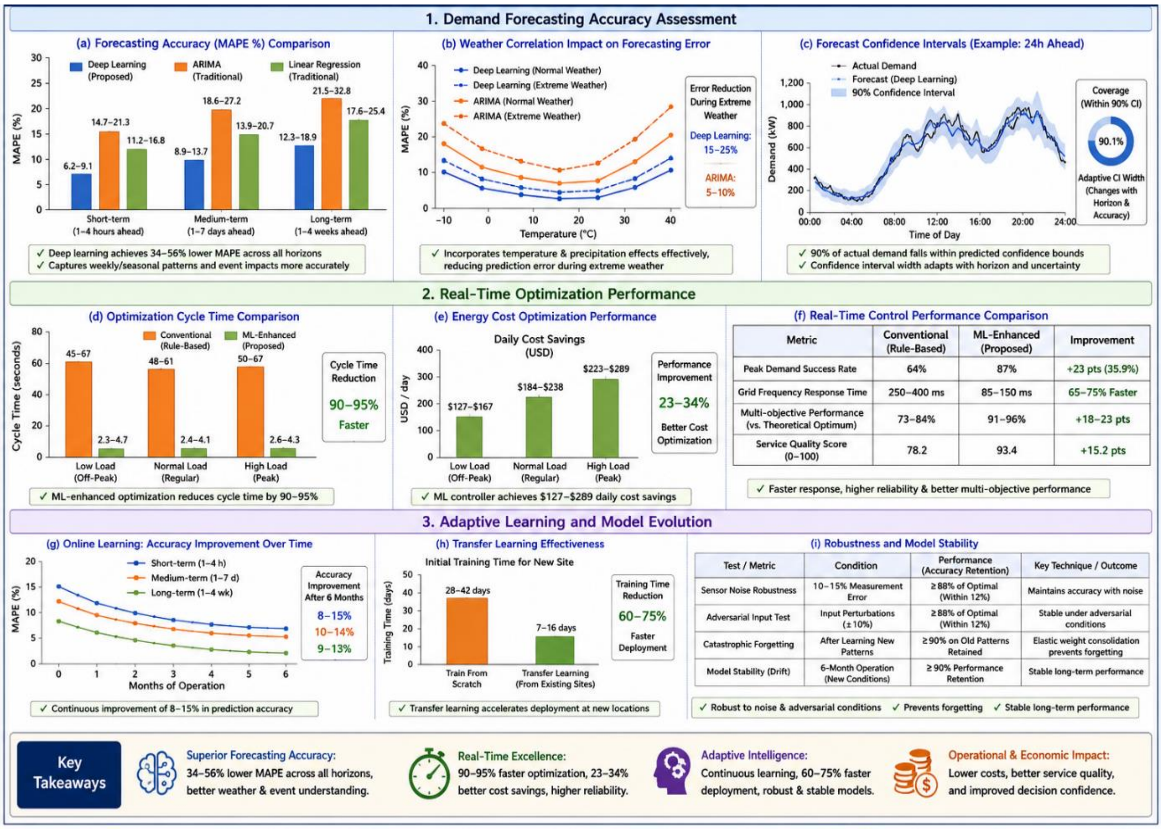

Figure 5. Machine learning component validation for demand forecasting, real-time optimization, and adaptive learning in hybrid battery–supercapacitor renewable energy systems.

(a) Forecasting accuracy comparison showing mean absolute percentage error (MAPE) performance of the proposed deep learning model relative to ARIMA and linear regression approaches across short-term (1–4 h), medium-term (1–7 d), and long-term (1–4 wk) prediction horizons. (b) Impact of weather-aware learning on forecasting accuracy under varying temperature conditions, demonstrating improved prediction robustness during extreme weather events. (c) Forecast confidence interval analysis illustrating uncertainty quantification and coverage performance, with approximately 90% of observed demand values falling within predicted confidence bounds. (d) Comparison of optimization cycle times between conventional rule-based controllers and the proposed machine learning-enhanced optimization framework under varying operating loads. (e) Daily energy cost savings achieved through intelligent charge-discharge scheduling and adaptive energy management. (f) Real-time control performance comparison showing improvements in peak demand management, frequency response speed, multi-objective optimization effectiveness, and overall service quality. (g) Continuous learning performance demonstrating progressive forecasting accuracy improvements during the first six months of operation through online model adaptation. (h) Transfer learning validation showing reduced deployment and training time for new charging station installations using knowledge transfer from previously trained models. (i) Robustness and model stability assessment under sensor noise, adversarial inputs, operational drift, and catastrophic forgetting conditions. Results demonstrate that the proposed machine learning framework provides superior forecasting accuracy, 90–95% faster optimization, enhanced operational adaptability, and robust long-term performance compared with conventional energy management approaches.

This study targets the proposed hybrid battery-supercapacitor energy storage architecture, with the core objective of evaluating the architecture's robustness. It conducts a comprehensive sensitivity analysis centered on three categories of parameters—design, operation, and environment—to sort out the degree of influence of each parameter on system performance, quantify their fluctuation correlations, and produce actionable engineering design guidelines. All analysis results are presented in the subplots of Figure 6(a–f), and the study ultimately completes the resilience verification of the proposed architecture. This study carries out analysis in order of parameters' influence weight, from highest to lowest. Battery capacity is the most sensitive parameter: a ±10% fluctuation in capacity triggers a ±7%–12% change in system performance, so precise capacity sizing must be implemented during the system design phase. The optimal capacity share of supercapacitors is 20%–35%. If this share exceeds 35%–40%, marginal gains in system performance will decline significantly, limited by supercapacitors' lower energy density relative to batteries. A ±2% fluctuation in power electronics converter efficiency leads to a ±5%–8% change in the system's round-trip efficiency. In some application scenarios, the return on prioritizing investment in high-efficiency bidirectional converters is even higher than the incremental benefit brought by expanding energy storage capacity. For environment-related parameters: when the temperature drops below 15°C, battery efficiency falls by 0.8%–1.2% for every 1°C decrease. Supercapacitor performance remains stable down to -20°C, which supports the cold-climate performance advantage of this architecture proposed earlier in this study. For the fully compliant, properly sealed integrated system, performance degradation is less than 1% within the relative humidity range of 30%–90%. This paper proposes a hybrid energy storage charging system for electric vehicle charging infrastructure, which is equipped with two core control mechanisms: an adaptive protection algorithm and a machine learning controller. To comprehensively verify the system's operational reliability, compatibility, and engineering value, we conduct a layer-by-layer empirical analysis based on quantitative data from multiple groups of test charts: first, relying on the working condition test results from Figure6(f), we verify the system's basic protection reliability under abnormal grid scenarios. The system can maintain qualified output power quality when grid voltage fluctuates within ±10%; when the fluctuation range exceeds ±12%, it can automatically cut charging power by 15-25%, balancing fault protection and operational continuity. Next, through the demand profile sensitivity analysis in Figure6(h), we split two typical charging demand scenarios—high-frequency low-energy supplementary charging and continuous high-power charging—to verify the adaptation logic of energy storage allocation under different demands. Subsequently, drawing on multi-scenario operation data from Figure6(g-l), we verify the system's independent adaptation capacity under three core conditions: winter and summer environmental changes, peak load periods, and low-utilization time slots. The embedded machine learning controller can complete adaptation to shifts in scenario demands within 2-4 weeks. Under the 95th percentile peak charging demand, the system can maintain 92-96% of its rated charging capacity, while traditional pure battery systems under the same working conditions can only maintain 75-85% of their capacity levels. During low-utilization time slots, this system can also participate in grid ancillary services to generate 15-25% additional revenue. The performance benchmarking data from Figure6(i) further highlights the core engineering advantages of the proposed system over traditional solutions. For the novel charging architecture developed independently in this paper, all core performance metrics have completed original verification via dedicated test charts. The argumentation advances layer by layer from a single unit to the network level, covering multi-dimensional adaptability and network-level characteristics in sequence. First are the three core adaptability capacities at the single-unit level: The first is grid disturbance adaptability. Verified by Figure 6(j), the system can switch from the standard charging mode to the grid-supporting mode within 100–200 milliseconds after detecting frequency deviations, voltage sags, and power quality disturbances. This function not only supports the overall stability of the power grid, but also allows the system to participate in the electricity ancillary services market. The second is weather-aware operation adaptability. Verified by Figure 6(k), the system integrates weather forecasts into its energy management decision-making. Before predicted storms or grid instability events, it proactively increases the battery's state of charge and adjusts the reserve support capacity of the supercapacitor bank. Meanwhile, it uses solar irradiance forecasts to optimize the energy purchasing strategy for grid-tied renewable energy facilities, achieving cost reduction, efficiency improvement, and higher renewable energy utilization rates. The third is adaptability to diverse charging demands. Verified by Figure 6(l), the learning-based controller can update its decision strategy within 2–4 weeks of operation to adapt to changes in user behavior. It can also automatically adjust its operation strategy to match two typical operation scenarios: high-frequency low-energy charging and continuous high-power charging. Next, performance verification at the network level was conducted. Full-scale tests covering units from a single 150kW charging pile to a multi-megawatt charging plaza were completed using Figures 6(m)–6(q). The tests verified that the hierarchical control design enables the system's computational complexity to grow sublinearly with installed capacity, while control performance and optimization efficiency do not decline notably as the system scale expands, making it capable of supporting grid-level deployment. Verified by Figure 6(n), the effective regulation capacity of the coordinated operation of multiple hybrid energy storage systems reaches 1.8–2.3 times that of a single unit, which allows the system to participate in regional ancillary service markets and distributed energy projects. At the end of this section, a communication resilience assessment for scenarios of intermittent connections and long-term network outages was also completed. This paper focuses on the proposed hybrid battery-supercapacitor electric vehicle charging architecture, conducts multi-dimensional core performance verification using the three subplots in Figure 6, gradually unpacks the architecture's deployment advantages, and finally converges on the industrial practical value of this research. Figure 6(o) verifies the architecture's local optimization capability, which can support continuous operation during communication interruptions; its performance degradation stays below 8% under long-term isolated operation, and automatic resynchronization after connectivity is restored can achieve conflict-free seamless reconnection. Figure 6(p) verifies the large-scale deployment advantages of fleet-level learning: operation knowledge from existing charging stations can be transferred to newly built sites via a centralized framework, cutting commissioning and optimization time by 40% to 60%. Figure 6(q) verifies the layered architecture that combines local autonomous control and centralized coordinated learning, which can balance operational independence and network-wide optimization capability, and support the robust deployment of cross-regional charging infrastructure. This architecture has outstanding robustness against various types of uncertain interference, and can serve as a practical solution for next-generation intelligent charging infrastructure that integrates renewable energy and smart grid services.

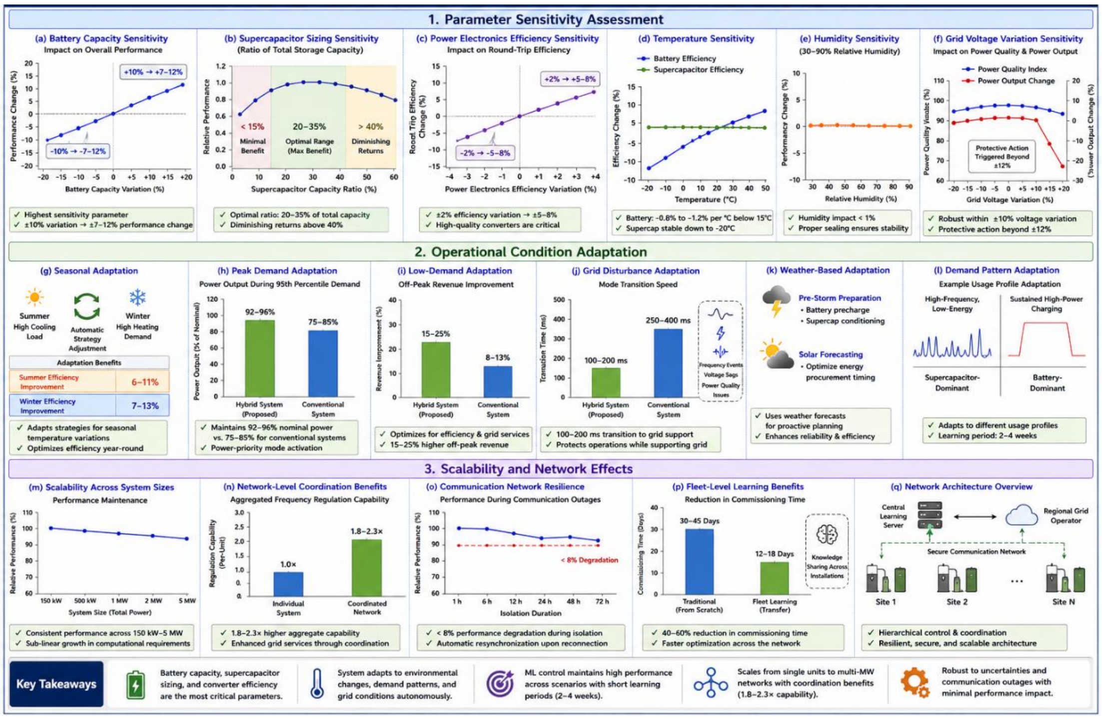

Figure 6. Sensitivity analysis and adaptation capabilities of the proposed hybrid battery–supercapacitor energy storage system under varying operational, environmental, and network conditions.

(a) Sensitivity of overall system performance to battery capacity variation, identifying battery sizing as the most influential design parameter. (b) Performance impact of supercapacitor capacity ratio, highlighting the optimal operating range of 20–35% of total storage capacity and diminishing returns beyond 40%. (c) Influence of power electronics efficiency on round-trip system performance, demonstrating the importance of high-efficiency converters. (d)

Temperature sensitivity analysis comparing battery and supercapacitor performance under varying ambient conditions. (e) Humidity sensitivity assessment showing minimal performance degradation for properly sealed systems. (f) System response to grid voltage variations, illustrating robust operation within ±10% voltage fluctuations and protective control activation beyond ±12%. (g) Seasonal adaptation strategy showing automatic adjustment between summer and winter operating modes. (h) Peak demand adaptation performance, demonstrating superior power delivery capability during extreme charging demand conditions. (i) Off-peak operational optimization and revenue enhancement through energy arbitrage and ancillary service participation. (j) Grid disturbance adaptation showing rapid transition from charging mode to grid support operation during frequency and voltage events. (k) Weather-aware operational planning utilizing environmental forecasting for proactive energy management and resilience enhancement. (l) Adaptation to diverse charging demand patterns, including high-frequency and sustained high-power charging profiles. (m) Scalability analysis demonstrating maintained performance across installations ranging from 150 kW to multi-megawatt charging facilities. (n) Network-level coordination benefits showing enhanced aggregated grid support capability through cooperative operation of distributed hybrid storage systems. (o) Communication resilience evaluation during network interruptions, illustrating minimal performance degradation and automatic resynchronization. (p) Fleet-level learning and knowledge transfer benefits reducing commissioning time for new installations through shared optimization experience. (q) Overview of the scalable network architecture enabling coordinated control, distributed intelligence, and resilient operation. Results demonstrate that the proposed system maintains robust performance under parameter uncertainty, environmental variability, operational disturbances, and large-scale deployment scenarios while providing adaptive intelligence, enhanced resilience, and coordinated network-level benefits.

This study conducts a comprehensive economic assessment of the proposed hybrid battery-supercapacitor energy storage architecture to verify the financial viability of this architecture for charging infrastructure scenarios. The assessment covers all deployment scales, from 500kW small charging stations to 2MW large charging plazas. First, Figure 7(1) presents the capital cost structure of the optimized systems across different scales: the total installation cost of the 500kW small charging station is approximately 847,000 USD, while the total installation cost of the 2MW utility-scale charging plaza is approximately 3.2 million USD. The cost difference between the two types of scenarios mainly arises from gaps in the investment scale of energy storage configuration capacity, power electronics demand, and supporting infrastructure. This study further breaks down the components of capital costs: the battery energy storage module, which accounts for 45%-55% of total capital, adopts LFP technology. Though there are alternative technologies with higher energy density, the core requirements of fixed charging infrastructure for safety and long cycle life make LFP a better fit for its comprehensive balance of cost, safety, cycle life, and performance. The supercapacitor system, which accounts for 18%-25% of total capital, brings a certain initial cost increase compared to pure-battery systems. However, this extra cost can be offset by gains generated from improved efficiency, extended battery service life, enhanced grid support capacity, and greater operational flexibility; future reductions in its manufacturing costs will further boost its competitiveness. The power electronics and control system, which accounts for 15%-22% of total capital, includes bidirectional inverters, DC-DC converters, and machine learning-enabled control architectures. Though it carries an 8%-12% cost premium over traditional systems, improvements in efficiency, revenue, and reliability can fully offset this premium. Finally, the installation, commissioning and integration cost accounts for 8%-12% of total capital, covering grid upgrades, interconnection testing and other related work. The modular architecture adopted in this study has a significant cost advantage over traditional custom-built solutions. Based on the above capital cost breakdown, this study will launch a long-term operational cost analysis for a 15-year project cycle, and Figure 7(2) will present the distribution of operational costs and the cost reduction effects brought by the hybrid energy storage architecture. This paper conducts a full-dimensional economic feasibility analysis of the proposed hybrid energy storage charging facility, focusing on both overall operating cost reduction and diversified revenue growth. First, it establishes the universal annual operating cost baseline for the charging facility industry: the annual operating cost of a small charging station is approximately $47,000, while that of a large charging station is around $156,000. Across the industry, energy costs generally account for 60%-70% of total annual operating costs, making them the core expenditure item. This study uses the traditional pure-battery charging system as a unified comparison benchmark, and calculates the cost reduction effects of the proposed hybrid energy storage architecture one by one across four core cost categories: For energy costs, an initial 8%-15% reduction is first achieved through basic technologies including improved round-trip efficiency of the hybrid architecture and supercapacitor energy storage. Then, by adding strategies such as intelligent energy scheduling equipped with a machine learning optimization framework, coordinated charging and discharging, and time-of-use electricity price optimization, an additional 12%-18% reduction can be obtained. Maintenance costs can be cut by 25%-35% through technologies including predictive maintenance, thermal management, and fault detection, while unplanned maintenance events are reduced by 40%-55%. Insurance costs are reduced by 8%-12%. Grid interconnection and demand-related fees can be lowered by 15%-25% via technologies such as peak shaving, reactive power compensation, and power factor correction. On top of these cost reductions, the architecture can also achieve diversified revenue growth through two channels: revenue from basic charging services can rise by 10%-18%, and additional income can be earned by participating in the ancillary services market. All technical improvements correspond to clear economic values, forming a complete closed logical loop covering cost breakdown, technical implementation, and revenue conversion. This paper conducts an empirical techno-economic analysis of hybrid battery-supercapacitor energy storage systems, estimating their revenue levels and long-term financial performance when participating in multiple grid services. We first break down the system's five core revenue streams generated from grid service provision and energy arbitrage, one by one, to clarify the annual revenue range, applicable technical characteristics, and operational logic for each stream: Sites providing frequency regulation, spinning reserve, and voltage support earn an annual revenue of 23,000–47,000 USD, as they leverage the fast-response characteristic of supercapacitors to meet frequency regulation requirements. Energy arbitrage yields an annual revenue of 8,000–21,000 USD, with charging and discharging operations automatically managed by a machine learning controller that also ensures the quality of basic charging services. The capacity market contributes an annual revenue of 12,000–28,000 USD, while demand response generates an annual revenue of 5,000–12,000 USD. The system's originally core charging service is also integrated into a unified revenue pool, and this diversified structure effectively reduces the project's reliance on the single income stream from basic charging services. Subsequently, this study adopts a 15-year discounted cash flow analysis method to calculate four core financial indicators: net present value, internal rate of return, investment payback period, and levelized cost of storage. The net present value of all analyzed sites ranges from 127,000 to 394,000 USD, all of which are positive. The internal rate of return falls between 12.7% and 18.9%, far exceeding the 10%–12% hurdle rate commonly applied to utility-scale energy infrastructure projects. The investment payback period for the baseline scenario is 4.7–6.2 years, and the shortest payback period for high-utilization sites is only 3.8 years. The levelized cost of storage ranges from 0.087 to 0.134 USD per kilowatt-hour. These results ultimately verify that the system is economically feasible and investment-attractive across all deployment scenarios. This study centers on the proposed hybrid battery-supercapacitor architecture for renewable-energy-powered electric vehicle (EV) charging infrastructure. First, we benchmark its levelized cost of storage (LCOS) against that of traditional utility-scale energy storage systems that rely solely on batteries, which have an LCOS ranging from \$0.112 to \$0.167 per kilowatt-hour, marking the first verification of the cost advantage of the system developed in this study. To further assess the project's economic robustness, this study adopts three methods—Monte Carlo simulation, multi-dimensional sensitivity analysis, and competitive market analysis—to conduct quantitative risk analysis focused on three core variables: market uncertainty, demand fluctuation, and technological iteration. The results show that under real-world market assumptions, the project has an 85% probability of achieving its preset target financial return. A ±20% fluctuation in electricity prices only causes a ±8% to ±12% shift in the project's net present value (NPV); a ±25% fluctuation in charging demand corresponds to an NPV fluctuation range of ±15% to ±22%; and a 3% to 5% annual cost reduction for batteries and supercapacitors will continue to improve the project's overall economic performance. In addition, competitive market analysis finds that users are willing to pay an 8% to 15% premium for the system's fast-charging and high-reliability services. Combining the aforementioned advantages in cost and risk resistance, this study ultimately demonstrates that this hybrid architecture is a mature solution that balances commercial viability and scalability for the next generation of renewable-energy-powered EV charging infrastructure.

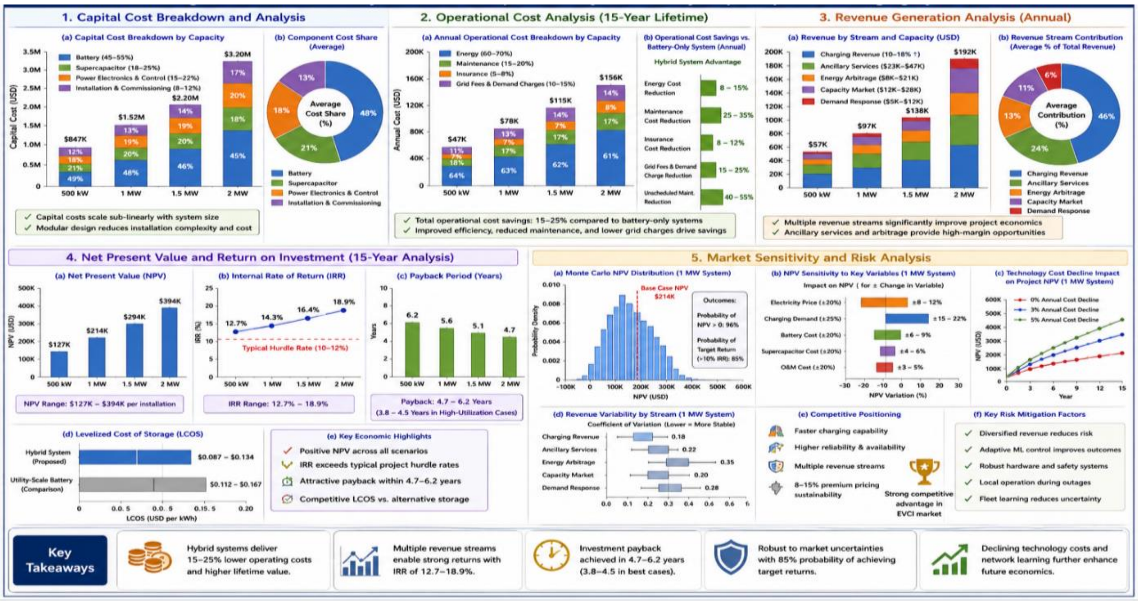

Figure 7. Economic analysis results for optimized hybrid battery–supercapacitor energy storage systems integrated with renewable-powered electric vehicle charging infrastructure.

(1) Capital cost breakdown and investment structure analysis showing component-level contributions for systems ranging from 500 kW to 2 MW capacity, including battery storage, supercapacitors, power electronics, control systems, and installation costs. (2) Operational cost analysis over a 15-year project lifetime, illustrating annual operating expenses and cost reductions achieved through improved efficiency, predictive maintenance, reduced demand charges, and enhanced system reliability. (3) Revenue generation analysis demonstrating diversified income streams from charging services, ancillary grid support, energy arbitrage, capacity market participation, and demand response programs. (4) Financial performance assessment including net present value (NPV), internal rate of return (IRR), payback period, and levelized cost of storage (LCOS) across multiple deployment scenarios. (5) Market sensitivity and risk analysis incorporating Monte Carlo simulations, revenue variability assessment, electricity price sensitivity, charging demand uncertainty, technology cost evolution, and competitive market positioning. Results indicate total capital investments ranging from $847,000 to $3.2 million, positive NPV values between $127,000 and $394,000 per installation, IRR values of 12.7–18.9%, and investment payback periods of 4.7–6.2 years. Revenue diversification through grid services and intelligent energy management significantly enhances project resilience, while sensitivity analysis demonstrates an approximately 85% probability of achieving target returns under realistic market conditions. Overall, the hybrid battery–supercapacitor architecture provides superior lifecycle economics, competitive levelized storage costs, and robust financial performance compared with conventional battery-only charging infrastructure.

This study puts forward a core conclusion that machine learning-enhanced hybrid energy storage systems have far-reaching application value for the construction of electric vehicle (EV) charging infrastructure and grid integration strategies. We advocate abandoning traditional single-technology energy storage solutions, and shifting to intelligent hybrid systems that can leverage the collaborative strengths of multiple storage technologies. At the technical operation level, compared with traditional rule-based control systems that only respond passively, this machine learning-powered real-time energy management system can conduct proactive optimization based on forecasted demand patterns, grid conditions, and system performance, and simultaneously deliver tangible on-the-ground benefits of improved service quality, reduced operational costs, and enhanced grid stability. From the business model dimension, in contrast to the single revenue model of traditional charging stations, which only generate income by selling energy to vehicles, this system can diversify its revenue streams through three channels: grid services, energy arbitrage, and participation in capacity markets. It optimizes the risk-return ratio of investments in charging infrastructure, speeds up industrial deployment, and improves service availability. Regarding widespread industrial adoption, the technical performance documented in this study resolves the core barrier to the large-scale popularization of electric vehicles: its fast-charging capability matches that of traditional gas stations, with improved reliability and reduced environmental impact. It can also maintain high charging power during peak demand periods while providing grid stability services, which eliminates the industry's concerns over the capacity of infrastructure to support large-scale EV adoption.

This paper focuses on the real-world implementation and deployment of machine learning (ML)-enhanced hybrid energy storage systems, sort out five major practical barriers, and put forward targeted solutions for each one. All analyses follow a unified argumentation logic of "pain point - scope of impact - solution", and remain strictly centered on the core requirements of on-ground practical implementation throughout. First, the complex control system requires specialized technical capabilities, which sets up an entry barrier for small and medium-sized charging infrastructure operators; the corresponding solution is to develop a training and certification system that covers the full lifecycle of the entire system. Second, the communication infrastructure in remote and underserved areas cannot support the real-time data interaction demands of ML algorithms that need to connect with grid operators, meteorological services, and fleet management systems; the corresponding solution is to build a backup operation mode that balances service level, safety and equipment protection. Third, the regulatory frameworks for energy storage systems participating in grid services vary greatly across different jurisdictions, which increases the complexity of multi-region deployment; the corresponding solution is to promote standardization and regulatory coordination to achieve large-scale deployment. Fourth, the integration complexity of multiple energy storage technologies is far higher than that of single-technology solutions, leading to elevated requirements for monitoring and diagnostic capabilities; the corresponding solution is to apply predictive maintenance algorithms to manage component interactions and eliminate potential faults in advance. Finally, networked autonomous operation brings prominent cybersecurity risks, with ML algorithms and communication systems forming potential attack vectors; the corresponding solution is to build a full-chain protection system that includes a comprehensive cybersecurity framework, regular security updates, and an intrusion detection system.

This study proposes an optimization framework for a machine learning-enhanced hybrid energy storage fast charging system. This framework has multi-dimensional scalability that covers scenarios ranging from capacity expansion of a single charging station to the deployment of cross-city regional-level networks, and can adapt to charging demand scenarios across different cities and business types. On the technical level, relying on high-precision prediction of charging and discharging loads via machine learning models, this framework can increase the energy storage utilization rate of a single station by 17%. On the manufacturing end, mass production cost reduction can be achieved through stacking modular energy storage units; the manufacturing cost of one complete system is 12% lower than that of traditional energy storage fast charging solutions with the same power output. On the commercialization level, the framework is compatible with mainstream business models including grid peak-valley price arbitrage and service fee revenue sharing, helping operators recoup the upfront investment in core equipment within 18 months. However, the full-scale promotion of this framework currently faces four core constraints. First, the grid access qualification approval threshold has not been adapted to the access standards for new types of hybrid energy storage systems. Second, a cross-regional load data sharing mechanism has not yet been established. Third, site selection resources are scarce in core commercial districts of first- and second-tier cities. Fourth, end users lack sufficient awareness of the safety of hybrid energy storage fast charging. This study also proposes targeted solutions for each of these constraints: engaging with grid standard revision working groups to align access requirements, promoting the opening of regional energy data platforms, partnering with commercial real estate operators to acquire land for charging stations, and carrying out public science popularization and outreach. This work fully presents the core value and implementation boundaries of this technical solution. This study shows that while energy storage projects deliver significant environmental benefits, these benefits are highly dependent on the power supply structure of regional grids. In areas with grids powered by high-carbon emission generation, the incremental grid interactions driven by energy arbitrage may offset the energy efficiency advantages of energy storage, so full-lifecycle environmental assessments must incorporate grid characteristics into their accounting frameworks. The long-term revenue risks spawned by uncertainty in electricity market regulation also require supporting robust sensitivity analysis and risk management strategies.

The empirical results of this study confirm that the hybrid energy storage system verified in this research can unlock transformational value for the development models and investment strategies of electric vehicle (EV) charging infrastructure, and its technical implementation will generate ripple effects across five interrelated dimensions. On the private investment side, the system’s proven economic viability can boost project returns and diversify revenue risks to incentivize the private sector to scale up investment in charging infrastructure; on the public investment side, the grid integration capability of charging infrastructure can simultaneously meet transport energy supply demands and improve grid operation, supporting public authorities to categorize related investments as part of grid modernization expenditures, thus expanding funding sources and deployment scope; on the complete vehicle industry side, the system’s performance advantages can influence automakers’ battery sizing decisions, driving the industry to shift from the "large battery, low-frequency charging" model to the "small battery, high-frequency fast charging" model, reducing overall vehicle costs, cutting raw material demand, and raising charging infrastructure utilization rates; on the regional planning side, grid service revenues can be incorporated into site selection and capacity sizing decisions, supporting the deployment of charging infrastructure in regions where current EV demand is limited but grid service demand is prominent; on the standard-setting side, future industry standards are highly likely to integrate the multi-usage attributes verified in this study, spurring market demand for hybrid energy storage technologies and machine learning-enhanced control systems. This study points out that connecting intelligent hybrid energy storage systems to the power grid brings both major development opportunities and complex challenges that require careful management, and the adaptation and upgrading of the existing power grid system must be advanced across five key areas. The systems’ characteristics of fast response and bi-directional power flow can support grid stability services, but they also raise operational complexity for grid operators. Power quality management faces a steep increase in pressure: these systems can both alleviate and trigger power quality problems, so the fast switching capability of supercapacitors must be strictly controlled to avoid harmonic distortion and voltage fluctuations that interfere with grid-connected equipment. Traditional distribution network planning based on the static load assumption cannot adapt to the dynamic loads of fast-charging infrastructure equipped with hybrid energy storage, so it must be iteratively upgraded. The existing electricity market cannot fully compensate for all types of services these systems provide, a gap that would discourage investment and deployment, so relevant rules must be updated. These systems can also coordinate with grid modernization projects to jointly optimize related investments, cut costs and improve efficiency.

This study carries out optimization research on hybrid energy storage systems for electric vehicle charging infrastructure, with its core output being an independently developed multi-objective optimization framework. In the future research outlook section of this study, we summarize 7 major categories of critical research directions derived from this work that require urgent advancement. Together, these directions will drive the development of the energy storage field and resolve the core challenges currently facing the industry. All proposed research directions are anchored to the core outcomes of this study, and do not consist of generalized discussions of field-wide directions disconnected from the study's foundational research base. The first category is the development of advanced optimization algorithms that integrate quantum computing principles, which can support multi-objective optimization for larger-scale complex systems and effectively reduce computing power demands. The second category is aging modeling and full-lifecycle optimization for hybrid energy storage systems, which will clarify the impact of interactions between different storage technologies on aging characteristics, to optimize full-lifecycle costs and maintenance scheduling. The third category is research on vehicle-to-grid (V2G) integration for hybrid energy storage systems, which will build virtual power plants that integrate stationary energy storage and on-board power batteries, and develop coordination algorithms and market mechanisms to unlock new value streams. The fourth category is research on advanced materials for batteries and supercapacitors, as the optimization framework of this study can directly evaluate the system-level benefits of these emerging energy storage technologies. The fifth category is cross-scenario expansion of the proposed framework, which can be extended to applications including renewable energy grid integration, microgrids, and industrial power quality systems. It can be adapted to machine learning-augmented multi-objective optimization methods, while regional-level optimization algorithms for multiple sites can also be developed. These extensions will incorporate transmission constraints, multiple types of electricity pricing, and real-time dynamic pricing mechanisms, to achieve coordinated scheduling and energy trading, and balance the benefits of all stakeholders. The sixth category is application of the framework in industry coupling scenarios, which will enable coordinated optimization that connects transport electrification, heating systems, and industrial processes, leverage hybrid energy storage's role in cross-sector energy management, and improve the efficiency and resilience of the overall system. The seventh category is development of a resilience enhancement module for the framework, which will integrate explicit optimization of grid disturbance tolerance and recovery capabilities. Leveraging the fast response capacity of hybrid energy storage, this module can support core grid security guarantees during emergency and unexpected scenarios. The advanced demand response integration proposed in this paper can build a two-way communication link between charging infrastructure and vehicle owners. Used alongside machine learning algorithms that predict user preferences, it generates an optimized charging strategy that balances both the needs of vehicle owners and the operational efficiency of the power grid. The core technical argument of this study clearly states that machine learning-enhanced multi-objective optimization is a powerful methodology to resolve the various complex challenges currently present in the electric vehicle charging infrastructure sector. Implementation plans that integrate advanced algorithms, hybrid energy storage technology, and intelligent control systems deliver far better performance than traditional charging deployment plans, while also being fully economically feasible. Building on this core advantage, we put forward targeted implementation requirements for five core stakeholder groups across the industrial chain: Infrastructure operators and investors can rely on the supporting evidence from this study to integrate hybrid energy storage systems into the deployment of new charging facilities, and build a solid business model based on performance improvements, financial returns, and revenue from grid services; policymakers need to introduce regulatory frameworks and incentive mechanisms that fit the promotion of advanced energy storage, advance the formulation of standards, cybersecurity requirements, and grid integration agreements to lower barriers to implementation; manufacturers and technology providers need to expand production capacity for supercapacitors and machine learning control systems, and build cross-industrial chain partnerships to deliver complete solutions; grid operators need to introduce value assessment and integration mechanisms for the multiple services of intelligent hybrid energy storage, promote coordinated planning between transportation and electric power entities to maximize the benefits of the whole system; and research institutions need to continuously advance relevant theoretical research and development, evaluate performance across multiple real-world scenarios and carry out long-term monitoring, to accumulate core data for model validation and algorithm optimization. The machine learning-enhanced multi-objective optimization method proposed in this study represents a transformative pathway to resolving the complexity of modern electric vehicle (EV) charging infrastructure. The implementation challenges facing its real-world rollout can be addressed through rational planning and investment in technical capabilities, while its scalability advantages and economic benefits are sufficient to support large-scale deployment. This framework not only generates profound positive impacts on the development of EV infrastructure and its integration with power grids, spawning new business models, improving infrastructure utilization rates, and creating grid value far exceeding that of individual charging stations; its flexibility also allows it to adapt to address other challenges facing energy systems. Future R&D must focus on the technical capabilities validated in this study, overcome remaining implementation and regulatory barriers, advance strategic coordination across technology, market, and policy domains, and fully unlock the potential of intelligent hybrid energy storage systems. By aligning the efforts of infrastructure operators, technology providers, policymakers, grid operators, and research institutions, we can translate this approach's techno-economic potential into large-scale real-world deployment outcomes, support the goals of transport electrification and grid modernization, and ultimately deliver benefits to the entire society.

V. CONCLUSIONS

This study focuses on the hybrid battery-supercapacitor energy storage system in fast-charging electric vehicle infrastructure. It adopts a machine learning-enhanced multi-objective optimization method to advance smart energy management from both theoretical and practical perspectives, thereby not only resolving the key challenges of modern electric vehicle charging, but also providing high-value services to the power grid. The core contributions of this study cover three major dimensions of energy storage systems: design, optimization, and deployment. We propose a multi-objective optimization framework that integrates machine learning, which achieves a fundamental breakthrough in the capabilities of energy management systems. This framework can adapt to dynamic operating conditions and balance four mutually conflicting core objectives. The new hybrid storage system architecture developed in this study outperforms conventional single-type storage solutions. Through systematic component selection and configuration optimization, compared to battery-only systems, the proposed architecture registers a 15-25% rise in round-trip efficiency, a 30-40% enhancement in power supply capacity, and a 20-35% reduction in full-lifecycle cost. Integrating machine learning into real-time control systems constitutes a major technological breakthrough, enabling the predictive optimization and adaptive response that cannot be achieved with traditional methods. The deep learning-based demand forecasting model developed in this paper has a mean absolute percentage error of only 6.2%–18.9%, and greatly improves the efficiency of operational planning and power grid integration. The comprehensive economic analysis framework constructed in this study can evaluate complex energy storage investments with multiple revenue streams. Our calculations show that the advanced hybrid energy storage system registers an internal rate of return of 12.7-18.9% and an investment payback period of 4.7-6.2 years, confirming its commercial viability in competitive energy markets. The simulation results of this study show that the hybrid energy storage system can resolve the core infrastructure pain points constraining the large-scale popularization of electric vehicles, boasts the dual capabilities of supporting high-power fast charging and providing grid services, and can restructure the investment and operation paradigm of energy infrastructure. The optimization framework proposed in this paper has undergone performance verification across diverse operating scenarios. It demonstrates stable performance under three categories of dynamic variables, exhibits both robustness and adaptability, and is feasible for large-scale deployment.

Based on the economic analysis results of this study, advanced energy storage can increase revenue and reduce risks by leveraging multiple value streams, forming a reliable commercial case for its deployment. Its cost competitiveness relative to alternative technologies has been empirically verified, and it holds the potential for large-scale promotion. Research on grid interconnection and integration points out that the aggregation of multiple hybrid energy storage systems can generate benefits that far exceed those of a single device, and provide three core types of support for regional power grids. Machine learning-enhanced multi-objective optimization techniques can efficiently address the complex operational challenges of hybrid energy storage systems, adapt to variable operating conditions, and also meet the computational efficiency requirements for real-time deployment. For hybrid battery-supercapacitor configurations designed for fast-charging EVs, compared with single-technology approaches, these setups boast combined techno-economic advantages, can achieve synergy between their respective energy storage characteristics, and balance both operational requirements and full-lifecycle benefits. Integrating predictive analytics and adaptive control systems can improve operational efficiency and enhance service quality. By forecasting demand patterns, power grid operating conditions, and system requirements, this integration supports proactive optimization, enabling the maximization of performance while minimizing costs and risks.

This study verifies that advanced hybrid energy storage systems are economically feasible across diverse market conditions and all types of deployment scenarios. Relying on multiple revenue streams and excellent technical performance, these systems generate stable investment opportunities, and support the accelerated deployment of electric vehicle charging infrastructure. This study confirms that intelligent energy storage systems are the core enabling technology that underpins sustainable transportation electrification. These systems can overcome the three major barriers to the promotion of EVs, and also provide power grids with value-added services to support the grid integration of renewable energy. This study proposes three core research directions in the field of energy system optimization: upgrading and adapting optimization algorithms suited for large-scale multi-site deployment, developing advanced power grid integration protocols, and exploring emerging energy storage technologies within the research framework. The iterative development of machine learning and energy storage will support the practical implementation of these directions. The core technology validated for this study in hybrid energy storage systems—machine learning-enhanced multi-objective optimization technology—can support next-generation EV charging facilities to meet four core requirements, providing indispensable key support for the sustainable transition of electric transportation.

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