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Article

An integrated LSTM-MPA framework for intelligent hybrid renewable energy forecasting and charging optimization of campus electric bicycle and motorcycle systems

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Abstract: The increasing adoption of electric bicycles and motorcycles has intensified the demand for sustainable and reliable charging infrastructures, particularly in campus environments characterized by fluctuating mobility patterns and renewable energy variability. This study proposes an intelligent hybrid solar–wind renewable charging framework integrated with Long Short-Term Memory–Marine Predators Algorithm (LSTM-MPA) optimization to improve adaptive forecasting, charging stability, and renewable energy utilization. The methodology combined systematic meta-analysis and deep learning simulation approaches. A total of 30 empirical studies were analyzed using PRISMA-based selection procedures, risk-of-bias assessment, effect-size evaluation, and publication bias analysis. Experimental renewable energy datasets consisting of photovoltaic (PV), wind turbine, and charging parameters were modeled using the proposed hybrid LSTM-MPA architecture. The results demonstrated that Solar-Wind-Deep Learning systems achieved the highest average effect size of 20.653. The forecasting model achieved Root Mean Square Error (RMSE) values of 115.70–125.65 and Mean Absolute Error (MAE) values of 90.34–93.64, while training and validation losses decreased by more than 39%, indicating stable convergence. Operational analysis showed that hybrid renewable generation consistently exceeded campus charging demand, maintaining battery State of Charge (SoC) near 100% and resulting in a cumulative renewable energy generation of 43,235.30 kWh. Annual renewable energy exceeded 2,070 kWh with a maximum energy balance of 882.64 kWh. The system was economically feasible, achieving an IRR of 14.9% and positive cumulative cash flow after the seventh operational year, while reducing cumulative CO_2 emissions by more than 22,450 kg over 20 years.

Keywords: hybrid renewable energy; electric vehicle charging station; LSTM-MPA; solar-wind system; intelligent forecasting

1. Introduction

1.1. Research background analysis

The global transition toward sustainable energy systems has become one of the most critical scientific and technological priorities in modern energy research. Rapid industrialization, rising demand for urban mobility, and continued reliance on fossil-fuel electricity generation have significantly intensified environmental degradation and carbon emissions across multiple sectors [1, 2]. The transportation sector has emerged as a major contributor to greenhouse gas emissions due to the extensive use of conventional combustion-powered vehicles [3, 4]. In recent years, Electric Vehicle (EV) adoption has accelerated substantially due to growing environmental awareness, government decarbonization policies, and advances in battery technology. Among various EV categories, e-bicycle and e-motorcycle systems have gained considerable attention due to their lower operational costs, flexible mobility characteristics, and suitability for densely populated urban and campus environments [5, 6]. However, the growing penetration of EV technologies simultaneously increases electricity demand. It places substantial pressure on existing charging infrastructure, particularly in regions with unstable grid conditions and limited capacity for renewable integration [7,8].

The increasing deployment of EV charging stations introduces significant operational challenges associated with energy sustainability, power stability, and charging efficiency [9, 10]. Conventional grid-dependent charging systems remain highly vulnerable to electricity price fluctuations, peak demand instability, and carbon-intensive electricity production [11,12]. These limitations become more critical in campus environments, where charging demand patterns fluctuate dynamically with academic schedules, mobility activities, and distributed energy consumption behavior. Consequently, hybrid renewable charging architectures combining solar and wind resources have emerged as highly promising alternatives for decentralized EV charging applications. Solar energy offers stable daytime electricity generation potential, while wind energy provides complementary generation characteristics during low solar irradiance conditions [13, 14]. The integration of hybrid renewable resources, therefore, enables improved energy continuity, reduced grid dependency, and enhanced sustainability performance within EV charging infrastructures [15, 16]. Furthermore, intelligent coordination between renewable generation and charging demand becomes essential to maintain charging reliability under highly variable environmental conditions.

Recent technological developments have demonstrated that hybrid solar-wind systems can substantially improve renewable penetration and energy resilience within smart charging infrastructures. Multiple studies have shown that hybrid renewable architectures significantly reduce operational costs, increase renewable self-consumption, and enhance charging reliability. The classification of previous studies related to hybrid renewable charging systems, optimization approaches, energy production configurations, and major findings is summarized in **Table 1**. Existing investigations also show that integrating renewable generation with advanced control strategies can minimize reliance on the grid and optimize battery utilization under uncertain operational conditions. Nevertheless, renewable energy production remains highly intermittent because solar irradiance and wind speed fluctuate continuously across temporal and environmental conditions. Such uncertainty directly affects charging stability, battery scheduling, and power management performance within EV charging stations. Therefore, advanced forecasting and intelligent optimization frameworks are increasingly required to ensure adaptive, reliable operation of the charging system.

Table 1. Previous Studies Reference Approach Research Focus Energy Production and Main Findings on Hybrid Renewable EV Charging Systems.

Number studies	Approach/Method	Research focus	Energy/Electrical production	Main findings
1	HOMER-based techno-economic analysis and hybrid PV–wind sizing	Hybrid solar–wind EV charging station for highway applications	50 kW PV + 30 kW wind (80 kW total)	Nishanthy et al. [17] achieved an LCOE of approximately 0.12 USD/kWh and reduced NPC by about 18% compared with grid-only charging systems.
2	HOMER sizing and sensitivity analysis	Optimal sizing of a hybrid PV–wind EV charging station	20 kW PV + 15 kW WT (35 kW total)	Ekren et al. [18] reduced NPC by around 22% compared with diesel-based systems and achieved an LCOE near 0.14 USD/kWh.
3	Multi-objective optimization using Genetic Algorithm (GA)	Hybrid PV–wind EV charging station with battery storage	60 kW PV + 40 kW WT + 100 kWh BESS	He and Wu [19] reduced CO_2 emissions by approximately 45% and achieved 92% renewable energy penetration.
4	Deep learning forecasting using LSTM and CNN integrated with BESS sizing	PV forecasting and battery sizing for EV charging stations	80 kW PV + 200 kWh battery	Lalbiakhlua et al. [20] obtained a forecasting MAPE of about 3.5% and reduced grid power consumption by 15%.
5	Hybrid deep learning and swarm intelligence (SA + PSO)	Demand response and battery load management for EV charging	45 kW PV + 40 kWh BESS	Sulaiman and Mustaffa [21] reduced peak demand by approximately 28% and improved battery lifetime by 12%.
6	Deep Belief Network (DBN) with adaptive control	Smart EV charging using hybrid PV–wind energy	55 kW PV + 35 kW WT + 120 kWh BESS	Sahoo and Sivasubramani [22] increased renewable utilization by 24% and lowered grid cost by 18%.
7	ANN-based controller with Model Predictive Control (MPC)	PV-powered EV charging station control	30 kW PV	Singh and Kumar [23] improved charging efficiency by approximately 22% and achieved 89% renewable self-consumption.
8	Bilevel optimization for hybrid fast-charging systems	Fast EV charging station with PV, wind, and storage	75 kW PV + 45 kW WT + 150 kWh BESS	Kurian and Janamala [24] reduced charging time by around 20% and lowered grid dependency by 38%.
9	XGBoost and Reinforcement Learning framework	EV charging management in hybrid microgrid systems	60 kW PV + 30 kW WT + 100 kWh BESS	Esfahani et al. [25] reduced grid electricity cost by 26% and increased renewable penetration by 19%.
10	Deep Reinforcement Learning (DRL) scheduling	Intelligent scheduling for hybrid EV charging stations	50 kW PV + 30 kW WT + 80 kWh BESS	Bokopane et al. [26] lowered operational costs by approximately 31% compared with heuristic approaches.
11	LSTM-based EV demand forecasting	EV load prediction for hybrid charging systems	40 kW PV + 25 kW WT + 60 kWh BESS	Aduama et al. [27] achieved a MAPE near 4.2% and improved renewable utilization by 21%.
12	CNN–LSTM hybrid forecasting model	Forecasting PV–wind generation for EV charging	70 kW PV + 40 kW WT + 120 kWh BESS	Tsalikidis et al. [28] reached an NMAE of around 3.8% and reduced grid dependence by 23%.
13	Graph Convolutional Network (GCN) with DRL	Urban EV charging coordination in hybrid stations	25 kW PV + 15 kW WT per station cluster	Ghode and Digalwar [29] reduced grid peak demand by 27% and charging waiting time by 18%.
14	Deep Dyna-Reinforcement Learning	Energy scheduling for hybrid PV–wind charging parks	65 kW PV + 35 kW WT + 130 kWh BESS	Ghode and Digalwar [30] reduced operational costs by approximately 29% compared with MPC methods.
15	Neural-network-based energy controller	Hybrid solar–wind charging park optimization	100 kW PV + 60 kW WT + 200 kWh BESS	Ghenai et al. [31] improved system efficiency by 18.7% and increased average final SoC by 12.5%.
16	Random Forest and SVM-based demand response	Demand-response-enabled hybrid EV charging	50 kW PV + 30 kW WT + 100 kWh BESS	Anonto et al. [32] reduced peak grid demand by approximately 32%.

Table 1. *Cont.*

Number studies	Approach/Method	Research focus	Energy/Electrical production	Main findings
17	Simulation-based hybrid charging analysis	Fast EV charging station using PV and wind energy	40 kW PV + 25 kW WT	Koca [12] maintained a renewable contribution of about 94% during daytime operation.
18	Deep learning solar forecasting	Solar forecasting for EV charging parks with storage	120 kW PV + 180 kWh BESS	Yi et al. [33] reduced grid energy consumption by 19% through forecast-aware dispatch.
19	Comparative offshore and onshore hybrid design	Solar–wind e-bike charging station	5 kW PV + 5 kW WT (onshore) / 10 kW offshore WT	Afzal et al. [34] found that the offshore configuration produced 42% higher energy yield but had 15% higher LCOE.
20	GP-KHA deep learning optimization	Hybrid EV charging in smart microgrids	80 kW PV + 40 kW WT + 150 kWh BESS	Hassan [35] reduced operational costs by 14% compared with coordinated charging systems.
21	DQN-based reinforcement learning	Solar-driven residential EV charging optimization	20 kW PV + 50 kWh BESS	Sykiotis et al. [36] achieved 88.4% solar utilization and reduced electricity bills by 11.5%.
22	Ebola-inspired optimization with ML integration	Two-stage optimization for PV–wind charging stations	60 kW PV + 40 kW WT + 120 kWh BESS	Zhu et al. [37] reduced NPC by 27% and improved system reliability by 10%.
23	Neural-network-based SoC controller	Battery SoC control in hybrid charging stations	45 kW PV + 30 kW WT + 80 kWh BESS	Ofoegbu [38] extended battery cycle life by 15% and accelerated charging speed by 19%.
24	Deep learning fault detection and power management	Anomaly detection in hybrid charging stations	55 kW PV + 35 kW WT + 100 kWh BESS	Kumar Dhaked et al. [39] achieved fault detection accuracy above 95% and reduced downtime by 16%.
25	Deep learning capacity optimization	Capacity sizing and scheduling for wind–PV–battery systems	90 kW WT + 60 kW PV + 180 kWh BESS	Arjun et al. [40] achieved an LCOE of around 0.11 USD/kWh with a 96% renewable fraction.
26	Supervised learning using RF and SVM	Predictive EV charging behavior management	35 kW PV + 20 kW WT + 60 kWh BESS	P Sasidharan et al. [41] achieved prediction accuracy near 92% and improved renewable utilization by 18%.
27	ANN-fuzzy hybrid controller	Intelligent control of PV–wind EV charging stations	40 kW PV + 25 kW WT + 70 kWh BESS	Hakam et al. [42] improved charging efficiency by 19% and reduced grid dependency by 11%.
28	Deep Reinforcement Learning scheduling	Solar-powered e-bike charging station	10 kW PV + 20 kWh BESS	Chandra Mouli et al. [43] achieved 85% solar self-consumption and reduced grid costs by 30%.
29	Integrated PV-powered e-bike system	Hybrid solar e-bike charging concept	0.1 kW PV per vehicle	Binzaid and Kabir [44] increased stored energy by 33.3% within one hour and achieved a charging efficiency of 58.94%.
30	Dung Beetle Optimization with Spiking Neural Network (SNN)	Rapid battery charging using hybrid intelligent control	30 kW PV + 40 kWh BESS	Nirmala and Venmathi [45] reduced charging time by 24% and improved control accuracy.

In parallel with advances in renewable energy, deep learning technologies have become increasingly influential in modern smart energy systems, enabling them to model nonlinear, highly dynamic energy behavior. Various deep learning architectures, such as LSTMs, CNNs, DRL, and hybrid AI frameworks, have demonstrated strong predictive performance in renewable forecasting, charging scheduling, and energy optimization applications [46–49]. Intelligent forecasting systems enable charging infrastructure to anticipate variations in renewable energy availability and charging demand with greater accuracy than conventional statistical methods. The incorporation of adaptive AI-based prediction mechanisms also improves battery dispatch strategies, charging stability, and operational flexibility under fluctuating environmental conditions. In campus-scale charging environments, where energy demand exhibits strong temporal variability, predictive intelligence is essential for maintaining charging continuity while minimizing energy losses and operational costs. Consequently, integrating hybrid renewable charging infrastructure with intelligent deep learning frameworks represents a strategic pathway toward developing next-generation, sustainable, and adaptive EV charging ecosystems.

1.2. Research gap evaluation

Despite substantial progress in hybrid renewable charging technologies, existing studies still exhibit several scientific and technological limitations that restrict system adaptability and predictive robustness. Many previous investigations primarily focus on techno-economic optimization and static energy sizing, without incorporating adaptive forecasting intelligence to handle the highly nonlinear behavior of renewable energy systems. Although some studies have implemented AI-based prediction models, their integration with charging management frameworks often remains fragmented and insufficiently coordinated. Several optimization approaches also emphasize either renewable forecasting or charging scheduling independently, resulting in limited synchronization between energy generation prediction and real-time charging control. Moreover, numerous studies rely on single-model AI architectures that demonstrate inconsistent prediction accuracy under rapidly changing environmental conditions. These limitations reduce the operational reliability of hybrid charging infrastructures, particularly in campus environments where charging demand variability and renewable intermittency occur simultaneously.

Another critical limitation observed in previous studies is the lack of comprehensive intelligent frameworks that can integrate adaptive forecasting, multidimensional optimization, and energy stability management within a unified charging architecture. Existing AI-based charging systems often exhibit reduced robustness when exposed to uncertain weather patterns, fluctuating renewable generation, and stochastic charging demand. Furthermore, conventional optimization frameworks often have limited capability to balance charging efficiency, renewable penetration, battery stability, and operational cost simultaneously. The absence of hybrid intelligence mechanisms that combine advanced temporal learning and adaptive optimization also limits the capability of current charging systems to respond dynamically to real-time operational uncertainty. In addition, inconsistencies in forecasting precision across different renewable scenarios indicate that existing AI models still struggle to generalize effectively under diverse environmental conditions. Therefore, a more adaptive and integrated intelligent framework is required to improve forecasting reliability, charging stability, and the utilization of renewable energy within hybrid EV charging infrastructures.

1.3. Research novelty contribution

The existing literature has demonstrated significant progress in renewable energy-based EV charging systems through independent investigations of hybrid solar–wind generation, intelligent forecasting, energy management, and charging optimization. Several studies have successfully employed deep learning techniques, including Long Short-Term Memory (LSTM), to improve renewable energy forecasting. In contrast, others have applied metaheuristic algorithms to optimize charging scheduling and energy management. Nevertheless, these investigations generally address forecasting, optimization, techno-economic assessment, and renewable energy evaluation as separate research problems, resulting in fragmented analytical frameworks with limited capability to support integrated decision-making under highly dynamic operating conditions. Moreover, previous studies rarely combine systematic evidence synthesis via meta-analysis with experimental validation and intelligent optimization within a single methodological framework, making it difficult to evaluate both scientific evidence and practical charging performance comprehensively. To address these limitations, this study proposes a hybrid analytical framework that integrates meta-analysis, hybrid solar–wind renewable energy, Long Short-Term Memory (LSTM), and the Marine Predators Algorithm (MPA) into a unified intelligent charging architecture. By simultaneously incorporating evidence synthesis, renewable energy forecasting, adaptive optimization, and charging management, the proposed framework provides a more comprehensive analytical approach than existing studies. It establishes a stronger scientific foundation for intelligent renewable EV charging systems in campus environments.

The scientific novelty of this study is further demonstrated by the multidimensional integration of intelligent prediction, adaptive optimization, operational evaluation, and sustainability assessment within a single renewable-charging framework. Unlike previous studies that primarily evaluate forecasting accuracy or optimization performance in isolation, the proposed framework simultaneously analyzes renewable energy generation, charging demand dynamics, battery state-of-charge behavior, techno-economic feasibility, environmental impact, and system sustainability within a single integrated workflow. The hybrid LSTM-MPA architecture enhances temporal learning capabilities while adaptively optimizing forecasting parameters to improve operational robustness under stochastic solar irradiance, wind speed, and charging demand. Furthermore, the incorporation of a meta-analysis provides evidence-based justification for selecting the proposed intelligent framework. It situates the experimental results within the broader context of current research on renewable EV charging. This comprehensive integration goes beyond conventional algorithm development by providing a unified decision-support framework that improves renewable energy utilization, charging reliability, operational resilience, and long-term sustainability. Consequently, this study advances the current body of knowledge by bridging systematic evidence synthesis, artificial intelligence, hybrid renewable energy engineering, and practical campus-scale EV charging implementation within a single comprehensive analytical framework.

1.4. Research objectives

Based on the research gaps and scientific limitations identified in the previous subsection, this study aims to develop and comprehensively evaluate an intelligent hybrid renewable energy charging framework for campus-scale electric bicycle and motorcycle charging systems. Specifically, the objectives of this study are (1) to systematically synthesize and critically evaluate existing scientific evidence on hybrid renewable EV charging systems through a meta-analysis in order to identify current technological trends, methodological limitations, and future research opportunities; (2) to develop an integrated hybrid renewable charging architecture by combining solar photovoltaic and wind energy generation with Long Short-Term Memory (LSTM)-based renewable energy forecasting and adaptive parameter optimization using the Marine Predators Algorithm (MPA) for improving prediction robustness under stochastic operating conditions; (3) to experimentally evaluate the proposed framework in terms of forecasting performance, charging demand dynamics, renewable energy balancing, battery state-of-charge stability, techno-economic feasibility, and environmental sustainability using renewable energy data collected from a campus-scale charging environment; and (4) to establish a comprehensive decision-support framework capable of enhancing renewable energy utilization, charging reliability, operational resilience, and long-term sustainability while providing practical guidance for the implementation of intelligent renewable EV charging infrastructure. Collectively, these objectives provide a systematic foundation for bridging evidence-based scientific knowledge and practical renewable energy engineering and intelligent charging management, thereby advancing sustainable campus transportation systems.

2. Methodology

2.1. Methodological framework analysis

This study employed an integrated methodological framework combining analytical synthesis and intelligent simulation approaches to evaluate the implementation of hybrid renewable charging systems for electric bicycle and motorcycle applications in campus environments. The overall research workflow is illustrated in **Figure 1**, which shows the sequential integration of literature-based analytical evaluation and deep learning simulation. The initial stage consisted of a comprehensive literature review, followed by a meta-analysis to identify technological development, optimization trends, and predictive intelligence characteristics associated with hybrid solar-wind EV charging systems. The analytical synthesis stage involved risk-bias evaluation, forest plot analysis, and funnel plot assessment to assess the consistency, reliability, and distribution characteristics of findings from previous studies on renewable charging infrastructure and intelligent optimization systems. Following the analytical stage, experimental data were collected directly using solar PV systems and vertical wind turbine generators located in Semarang at coordinates 7° 00′ 43.44″ S and 110° 23′ 22.11″ T. The experimental dataset was specifically designed to support the deep learning case study on electric bicycle and motorcycle charging systems operating in campus environments with fluctuating renewable energy availability and dynamic charging demand.

The experimental dataset comprised multiple electrical and environmental parameters that captured the characteristics of hybrid renewable energy generation and charging output under real operational conditions. The measured variables included PV Voltage, PV Current, PV Power, Solar Irradiance Intensity, Wind Generator (WG) Voltage, WG Current, WG Power, Wind Speed, Wind Direction, Alternating Current (AC) Output Voltage, AC Output Current, AC Output Power, AC Output Frequency, and AC Output Energy. After data acquisition, the study implemented a hybrid deep learning framework that integrates MPA and LSTM to enable adaptive renewable energy forecasting and intelligent charging optimization. The MPA algorithm was used to optimize parameter search and adaptive learning performance. At the same time, the LSTM architecture was used to model the nonlinear temporal behavior associated with fluctuations in renewable generation and charging demand variability. All deep learning modeling, simulation, training, validation, and optimization processes were performed in Python to ensure computational flexibility, reproducibility, and efficient integration between the MPA optimization algorithm and the LSTM forecasting architecture. The training and validation process was subsequently performed to evaluate predictive robustness, forecasting precision, and adaptive learning capability under dynamic environmental conditions. The simulation stage further produced several analytical outputs, including training performance analysis, test data prediction performance, energy analysis, economic analysis, and environmental impact evaluation. These integrated analyses were ultimately used to establish a comprehensive intelligent charging framework that improves the utilization efficiency of renewables, charging stability, and adaptive forecasting performance for campus-scale hybrid renewable charging infrastructures.

2.2. Meta-analysis procedure

The study selection process was conducted systematically across multiple international scientific databases to ensure comprehensive coverage of relevant studies on hybrid solar-wind EV charging systems and deep learning-based intelligent optimization. The literature identification stage involved database searches in Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar using predefined search strings to capture studies on hybrid renewable charging infrastructure, intelligent charging systems, renewable energy forecasting, and AI-driven optimization. The overall identification and screening procedure is illustrated in **Figure 2**, which summarizes the sequential filtering process from database identification to final study eligibility assessment. Initially, 168 records were identified from the selected scientific databases before duplicate removal and screening. After removing 28 duplicate records, 140 studies remained for title and abstract screening evaluation. During the screening stage, 65 studies were excluded because they did not specifically address hybrid solar-wind charging systems, electric bicycle or motorcycle charging stations, or deep learning-based simulation and optimization frameworks. Subsequently, 75 full-text articles were assessed for eligibility, resulting in the exclusion of 45 studies that lacked quantitative performance indicators, did not employ predictive intelligence approaches, or were classified as conceptual, non-empirical investigations.

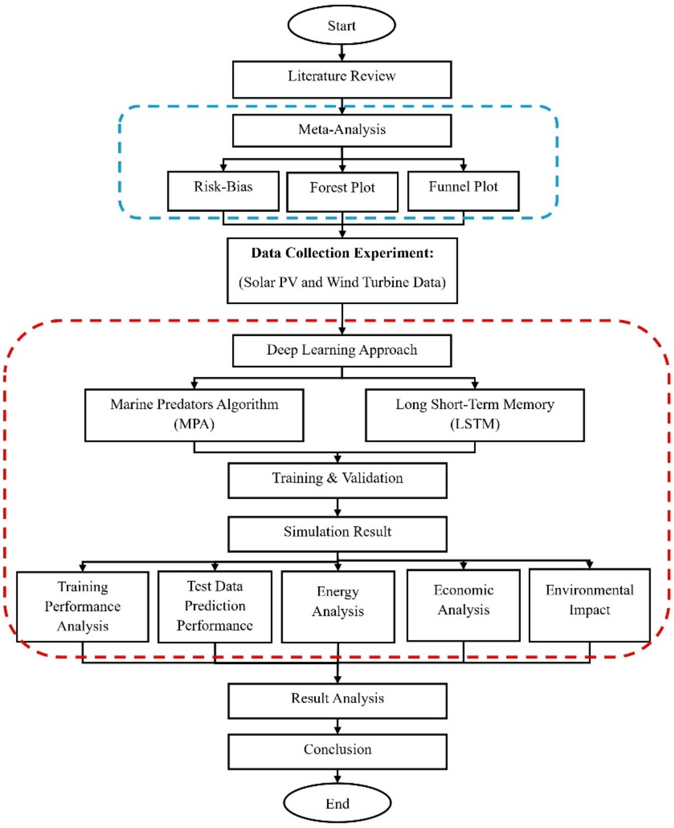


Figure 1. Integrated Meta Analysis and LSTM-MPA Deep Learning Framework for Hybrid Solar Wind Electrical Bicycle and Motorcycle Charging System.

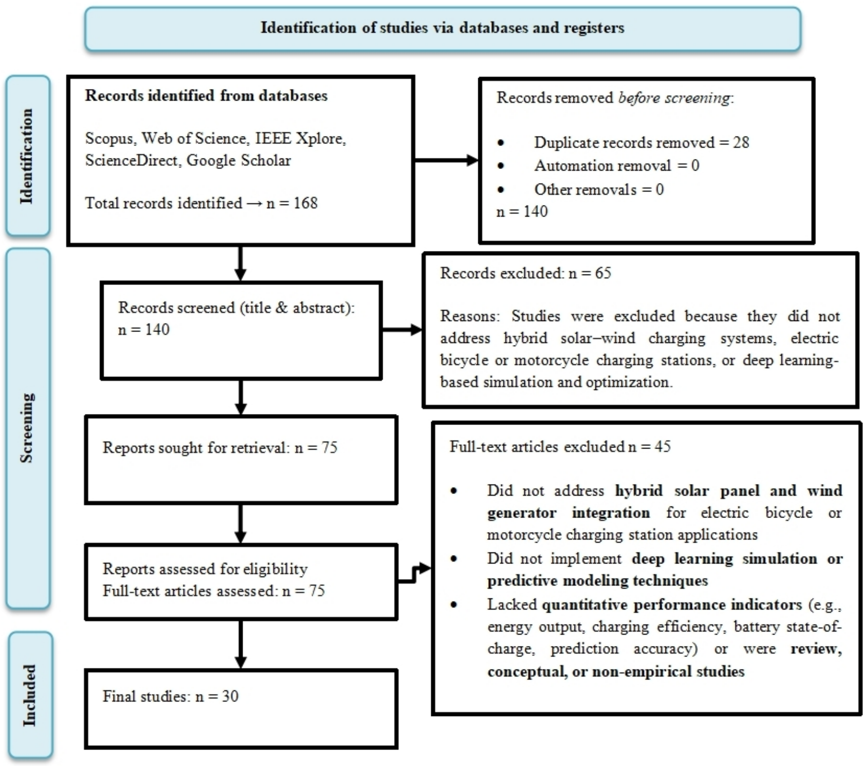


Figure 2. PRISMA-Based Literature Identification Screening, Eligibility, and Final Study Selection Process.

To improve methodological consistency and analytical rigor, the study implemented predefined inclusion and exclusion criteria during the literature selection process. The inclusion criteria comprised empirical studies on hybrid solar panel-wind generator integration for EV charging systems, intelligent charging optimization using deep learning, renewable energy forecasting applications, and studies reporting quantitative technical performance indicators such as charging efficiency, renewable energy output, SoC behavior, prediction accuracy, or operational optimization metrics. In contrast, exclusion criteria included studies unrelated to hybrid renewable charging systems, investigations lacking the implementation of AI or predictive intelligence, purely conceptual or review-based studies, and articles without measurable engineering performance indicators. In addition, quantitative synthesis procedures were conducted within a random-effects meta-analysis framework to assess the distributions of charging-efficiency effect sizes across heterogeneous studies. The pooled effect size was calculated using weighted mean estimation as presented in Equation (1) [50]:

$$\widehat{\theta} = \frac{\sum_{i=1}^{k} w_i \theta_i}{\sum_{i=1}^{k} w_i} \tag{1}$$

where $\widehat{\theta}$ represents the pooled effect size, θ_i denotes the individual study effect size, and w_i indicates the weighting factor assigned to each study. The weighting factor was determined based on the inverse variance approach using Equation (2) [51]:

$$w_i = \frac{1}{SE_i^2} \tag{2}$$

where SE_i represents the standard error associated with each study. Furthermore, the confidence interval boundaries for each effect size were estimated using Equation (3) [52]:

$$CI = \theta_i \pm 1.96 \times SE_i \tag{3}$$

The heterogeneity level among studies was subsequently evaluated using the Higgins heterogeneity index shown in Equation (4) [53]:

$$I^2 = \frac{Q - df}{Q} \times 100\% \tag{4}$$

where Q represents Cochran's heterogeneity statistic and df denotes the degree of freedom. Additionally, publication bias assessment was performed using regression-based asymmetry evaluation through Equation (5) [54]:

$$Y = \beta_0 + \beta_1 X + \varepsilon \tag{5}$$

where Y denotes the effect size distribution, X represents study precision, β_0 and β_1 correspond to regression coefficients, and ε indicates the residual error term. These integrated analytical procedures ensured statistical robustness, predictive consistency, and engineering relevance for hybrid renewable EV charging applications. As summarized in **Table 2**, the database search strings and predefined inclusion and exclusion criteria were applied to ensure methodological consistency and analytical rigor.

Table 2. Database Search Strings: Inclusion Criteria and Exclusion Criteria.

Database	Search strings	Inclusion criteria	Exclusion criteria
Scopus	"Hybrid Solar Wind EV Charging Station" AND "Deep Learning" AND "Electric Bicycle" OR "Electric Motorcycle"	Empirical studies related to hybrid renewable EV charging and deep learning optimization	Review papers, conceptual studies, and non-renewable charging systems
Web of Science	"PV Wind Charging System" AND "LSTM" OR "AI Forecasting" AND "Campus Charging"	Studies reporting quantitative charging and renewable performance indicators	Studies without predictive modeling or engineering analysis
IEEE Xplore	"Hybrid Renewable Charging Station" AND "Machine Learning" AND "Battery Optimization"	Studies implementing intelligent charging control or renewable forecasting	Pure hardware design without AI integration
ScienceDirect	"Solar Wind EV Charging" AND "Deep Learning Simulation" AND "Energy Management"	Studies discussing charging efficiency, renewable optimization, and forecasting	Studies lacking measurable technical outputs
Google Scholar	"Hybrid PV Wind Charging Station Deep Learning Electric Motorcycle"	Peer-reviewed studies related to renewable charging applications	Duplicate publications and non-empirical investigations

2.3. Deep learning architecture modeling

The proposed intelligent charging framework employed a hybrid LSTM-MPA architecture to improve the accuracy of renewable energy forecasting and to optimize adaptive charging under dynamic environmental conditions. The LSTM model was utilized to capture nonlinear temporal dependencies associated with solar irradiance fluctuation, wind speed variability, charging demand behavior, and hybrid renewable output instability [55–59]. In this study, the input sequence consisted of multivariate renewable energy and charging system parameters, including PV Voltage, PV Current, PV Power, Solar Irradiance Intensity, WG Voltage, WG Current, WG Power, Wind Speed, Wind Direction, AC Output Voltage, AC Output Current, AC Output Power, AC Output Frequency, and AC Output Energy (**Appendix Table A1**). For methodological transparency, a comparative overview of representative metaheuristic optimization algorithms, including Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Grey Wolf Optimizer (GWO), Differential Evolution (DE), Bayesian Optimization, and the selected Marine Predators Algorithm (MPA), is presented in **Appendix Table A2** to justify the selection of MPA for LSTM hyperparameter optimization. The proposed forecasting model employed a stacked LSTM architecture consisting of two hidden LSTM layers with 128 and 64 hidden units, respectively, followed by a fully connected output layer for one-step-ahead forecasting. A sequence length of 24 hourly observations was adopted, and the model was trained using the Adam optimizer with a learning rate of 0.001, a batch size of 32, a maximum of 100 training epochs, and early stopping with a patience of 10 epochs to improve convergence stability and prevent overfitting.

The computational structure of the proposed LSTM framework is illustrated in **Figure 3a**, which describes the sequential processing mechanism of the forget gate, input gate, candidate cell state, cell state update, output gate, and hidden state generation. The forget gate mechanism was mathematically formulated using Equation (6) [55]:

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \tag{6}$$

where f_t represents the forget gate activation, W_f denotes the weighting matrix, h_{t-1} indicates the previous hidden state, x_t corresponds to the current input vector, and b_f represents the bias parameter. Subsequently, the input gate was calculated using Equation (7) [56]:

$$i_t = \sigma\left(W_i[h_{t-1}, x_t] + b_i\right) \tag{7}$$

The candidate cell state generation process was determined using Equation (8) [57]:

$$\widetilde{C}_t = \tanh\left(W_c[h_{t-1}, x_t] + b_c\right) \tag{8}$$

The cell state updating mechanism was subsequently performed using Equation (9) [58]:

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C}_t \tag{9}$$

The output gate and hidden state generation were respectively calculated using Equations (10) and (11) [59]:

$$o_t = \sigma\left(W_o[h_{t-1}, x_t] + b_o\right) \tag{10}$$

$$h_t = o_t * \tanh(C_t) \tag{11}$$

where o_t represents the output gate activation and h_t denotes the hidden-state output used for renewable forecasting and charging prediction analysis. During model training, the Mean Squared Error (MSE) loss function was minimized. At the same time, a dropout rate of 0.20 was applied after each LSTM layer to reduce overfitting and improve model generalization under fluctuating renewable energy conditions.

To improve optimization capability and adaptive learning performance, the proposed LSTM architecture was integrated with the MPA optimization framework, as illustrated in **Figure 3b**. The MPA algorithm was employed to optimize parameter initialization, adaptive search exploration, convergence stability, and predictive learning efficiency within the renewable forecasting process [60–64]. Specifically, the Marine Predators Algorithm was used to optimize selected LSTM hyperparameters, including the learning rate, hidden unit configuration, and batch size, based on the forecasting objective function, thereby improving convergence behavior and predictive performance. Initially, the optimization procedure initialized predator populations randomly within the predefined search space using Equation (12) [60]:

$$X_i^0 \sim U(LB, UB) \tag{12}$$

where X_i^0 denotes the initial predator position, while LB and UB represent lower and upper search boundaries. During the optimization stage, the adaptive Fish Aggregating Devices parameter was updated using Equation (13) [61]:

$$\mathrm{FAD_t} = \mathrm{FAD_s} + \mathrm{t} \times \frac{(\mathrm{FAD_e} - \mathrm{FAD_s})}{\mathrm{Max_{iter}}} \tag{13}$$

The exploration phase for prey searching was formulated using Equation (14) [62]:

$$\mathrm{X_i^{t+1}} = \mathrm{X_t^{elite}} + \mathrm{R_B} \odot (\mathrm{X_{rand}} - \mathrm{R_A} \odot \mathrm{X_i^t}) \tag{14}$$

where $\mathrm{X_t^{elite}}$ represents the elite predator position, $\mathrm{X_{rand}}$ denotes random predator selection, and $\mathrm{R_A}$ and $\mathrm{R_B}$ correspond to adaptive random vectors. Furthermore, the exploitation phase for prey attacking behavior was expressed using Equation (15) [63]:

$$\mathrm{X_i^{t+1}} = \left(\mathrm{X_t^{elite}} - \mathrm{R_A} \odot (\mathrm{LB} + \mathrm{R_B} \odot (\mathrm{UB} - \mathrm{LB}))\right) \odot \mathrm{R_C} \tag{15}$$

The fitness evaluation process was subsequently performed using Equation (16) [64]:

$$\mathrm{f}\left(\mathrm{X_i^{t+1}}\right) = \frac{1}{\mathrm{N}} \sum\nolimits_{\mathrm{j=1}}^{\mathrm{N}} \left(\mathrm{y_j} - \widehat{\mathrm{y}}_\mathrm{j}\right)^2 \tag{16}$$

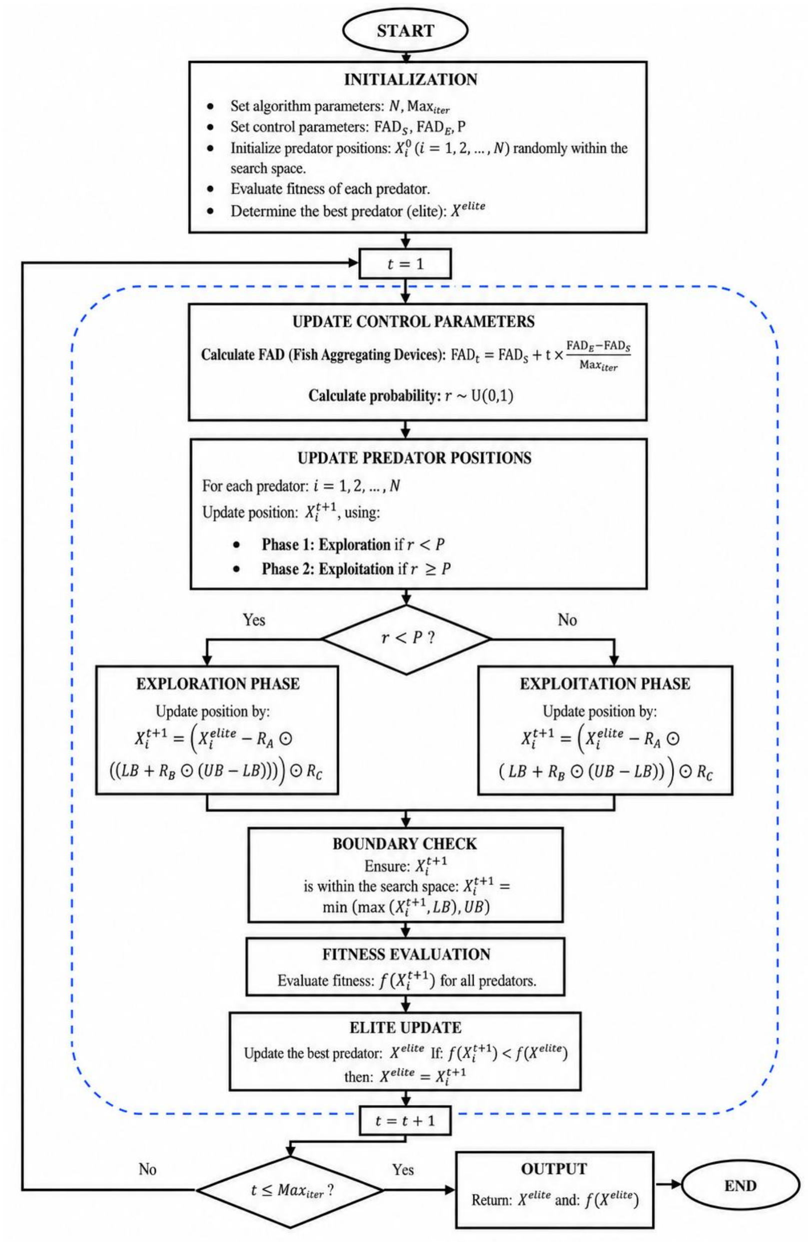
where $\mathrm{f}(\mathrm{X_i^{t+1}})$ represents the objective fitness value associated with forecasting accuracy and optimization performance. The elite predator update mechanism was then determined based on Equation (17) [65]:

$$\mathrm{X^{elite}} = \mathrm{X_i^{t+1}} \mathrm{iff}(\mathrm{X_i^{t+1}}) < \mathrm{f}(\mathrm{X^{elite}}) \tag{17}$$

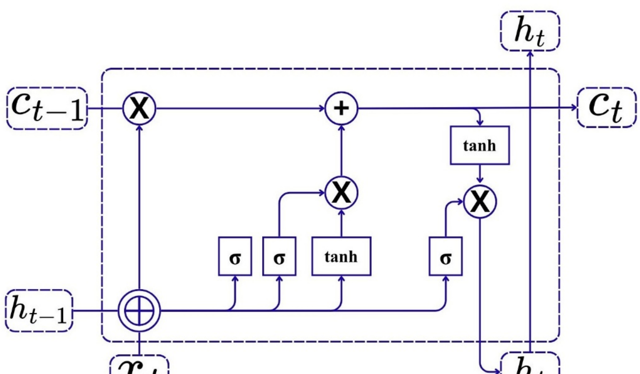
The hybridization of LSTM temporal intelligence and MPA adaptive optimization, therefore, enabled improved robustness, faster convergence, higher forecasting precision, and greater stability in renewable charging under fluctuating environmental conditions associated with campus-scale electric bicycle and motorcycle charging systems.

2.4. Hybrid charging system configuration

The proposed hybrid renewable charging configuration was designed to support sustainable charging for electric bicycles and motorcycles on campus, using integrated PV and wind energy conversion systems. The overall system architecture is illustrated in **Figure 4**, which shows the energy-flow interactions among the wind turbine subsystem, solar PV subsystem, AC/DC converter, battery storage unit, and EV charging station infrastructure. In the proposed framework, the solar PV subsystem generated DC electrical energy directly from solar irradiance, while the wind turbine subsystem produced AC electrical energy under varying wind speed conditions. The AC power generated by the wind turbine was subsequently converted to regulated DC power by the AC/DC converter before being integrated into the hybrid charging network. Simultaneously, the battery storage subsystem served as an adaptive energy-balancing unit to stabilize fluctuations in intermittent renewable energy and maintain charging continuity during periods of low renewable generation. The integrated charging architecture, therefore, enabled improved utilization of renewable energy, enhanced charging reliability, operational stability, and adaptive energy management for campus-scale EV charging applications under dynamically changing environmental conditions.



(a)



(b)

Figure 3. Hybrid LSTM Architecture and Marine Predators Algorithm Optimization Framework for Renewable Charging Prediction: **(a)** LSTM Computational Structure; **(b)** MPA Optimization Procedure.

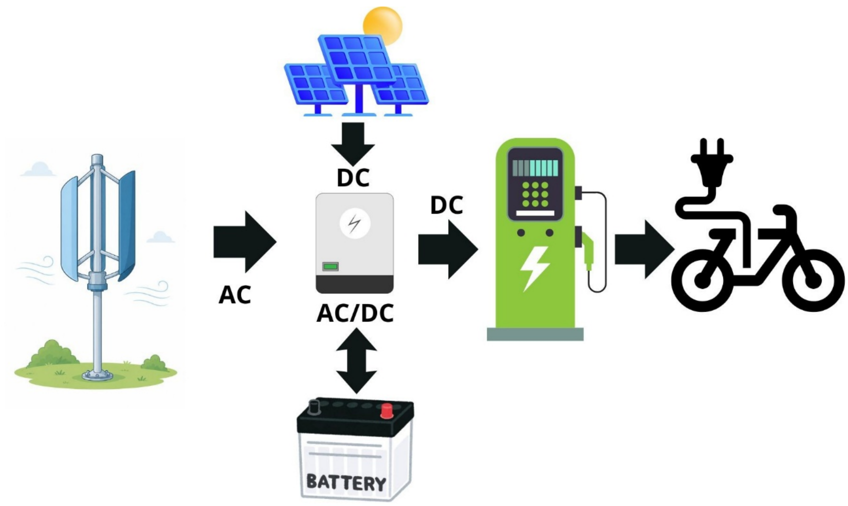


Figure 4. Hybrid Solar PV and Wind Turbine Integrated Charging System Architecture for Campus Electrical Bicycle Applications.

The technical specifications of the proposed renewable charging infrastructure are summarized in **Table 3**, including PV module characteristics, wind turbine parameters, battery storage configuration, inverter specifications, and economic assessment indicators. The PV subsystem employed monocrystalline silicon modules with a rated output power of 100 Wp and module efficiency of 21.3%, enabling enhanced solar energy harvesting performance under tropical environmental conditions. Furthermore, the wind energy subsystem employed an HAWT configuration with a rated power of 400 W and a rated wind speed of 12 m/s to complement renewable energy generation under fluctuating solar conditions. The battery storage subsystem implemented $LiFePO_4$ technology, with a storage capacity of 1.28 kWh and a round-trip efficiency of 95%, thereby supporting stable charging operations and improved retention of renewable energy. In addition, the hybrid inverter subsystem provided bidirectional energy conversion with 92–95% efficiency, enabling stable AC output-voltage regulation during EV charging. Economic parameters, including the inflation rate, discount rate, project lifetime, and annual O&M costs, were incorporated into the simulation framework to evaluate the long-term techno-economic feasibility and sustainability of the proposed intelligent hybrid charging system.

Table 3. Hybrid Renewable Charging System Technical Specification, Economic Parameter, and Energy Storage Configuration.

Category	Parameter	Value	Unit
PV Module Specification	PV Material	Monocrystalline Silicon	–
	Rated Power per Module	100	Wp
	Module Efficiency	21.3	%
	Power Temperature Coefficient (βp)	−0.35	%/°C
	Open Circuit Voltage (Voc)	26.48	V
	Short Circuit Current (Isc)	4.94	A
	Nominal Operating Cell Temperature (NOCT)	−45 to +85	°C
	Module Dimensions	760 × 670 × 35	mm³
	Initial Cost per PV Module	Rp 800,000	IDR

Table 3. *Cont.*

Category	**Parameter**	**Value**	**Unit**
Wind Turbine Specification	Turbine Type	Horizontal Axis Wind Turbine (HAWT)	–
	Rated Power	400	W
	Rated Wind Speed	12	m/s
	Cut-in Wind Speed	3	m/s
	Cut-out Wind Speed	25	m/s
	Rotor Diameter	1.2	m
	Hub Height	12	m
	Estimated Initial Cost	Rp 4,500,000	IDR
Battery Storage Specification	Battery Type	Lithium Iron Phosphate ($LiFePO_4$)	–
	Nominal Voltage	12.8	V
	Battery Capacity	100	Ah
	Storage Capacity	1.28	kWh
	Depth of Discharge (DoD)	80	%
	Cycle Life	4,000–6,000	Cycles
	Round-trip Efficiency	95	%
	Estimated Initial Cost	Rp 3,200,000	IDR
Inverter Specification	Inverter Type	Pure Sine Wave Hybrid Inverter	–
	Rated Power	1,000	W
	DC Input Voltage	12/24	V
	AC Output Voltage	220	V
	Output Frequency	50	Hz
	Conversion Efficiency	92–95	%
	Estimated Initial Cost	Rp 2,500,000	IDR
Economic and Financial Parameters	Inflation Rate in Indonesia (2026)	3.0	%
	Bank Indonesia Interest/Discount Rate	4.75	%
	Project Lifetime	20	Years
	Annual Operation and Maintenance (O&M) Cost	1–3% of Initial Cost	%/year

3. Results

3.1. Risk of bias and methodological quality assessment

The methodological quality assessment of the 15 studies included in the final meta-analysis demonstrated generally reliable evidence and acceptable analytical rigor for hybrid renewable EV charging research. Most studies were classified as low risk across key methodological domains, including randomization, deviations from intended interventions, missing data, measurement reliability, and selective reporting. As shown in **Figure 5a**, the majority adopted systematic experimental procedures and quantitative validation approaches to support reproducible, renewable charging analysis. Several investigations consistently applied AI-based optimization, renewable forecasting validation, and hybrid charging performance evaluation under dynamic operating conditions. However, moderate uncertainty remained in the randomization and selective reporting domains because some studies lacked transparent descriptions of optimization procedures and reproducibility. A few studies also showed limitations in handling missing data and maintaining measurement consistency when using highly stochastic renewable datasets. Overall, the findings indicate that current evidence strongly supports hybrid renewable EV charging research while highlighting the need for more standardized reporting and AI validation to improve methodological transparency and reproducibility.

The percentage distribution of methodological quality further confirmed the overall reliability of the selected studies. As shown in **Figure 5b**, the missing data domain had the highest proportion of low-risk studies, at approximately 66.67%, followed by the deviations and measurement domains at nearly 60%. These results indicate that most previous investigations employed stable data acquisition procedures and controlled simulation environments to reduce experimental inconsistencies. In contrast, the randomization and selective reporting domains showed slightly lower low-risk proportions of around 53.33%, reflecting moderate heterogeneity in AI model configuration, optimization settings, and forecasting evaluation strategies. This variation reinforces the need for the proposed hybrid LSTM-MPA framework, which is designed to improve adaptive robustness under fluctuating renewable resources and dynamic charging demand. Furthermore, the identified methodological heterogeneity underscores the need to integrate advanced forecasting, adaptive optimization, and unified charging control into future campus-scale EV charging systems. At the same time, the proposed framework directly addresses several limitations reported in previous studies.

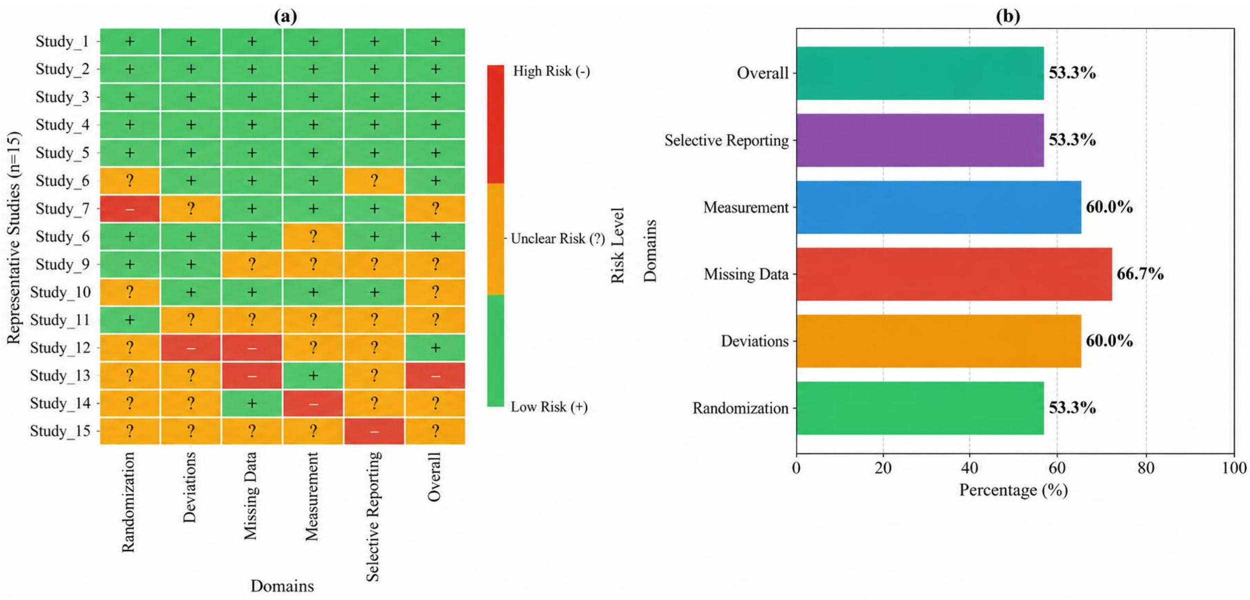


Figure 5. Risk of Bias and Methodological Quality of Hybrid Renewable EV Charging Studies: **(a)** Individual Risk-of-Bias Assessment; **(b)** Low-Risk Percentage Across Methodological Domains.

3.2. Effect size distribution and temporal performance evaluation of hybrid renewable EV charging systems

The meta-analysis of 30 selected studies identified clear differences in effect sizes across hybrid renewable EV charging technologies and AI-based optimization strategies. As shown in **Figure 6a**, the Solar-Wind-DL architecture achieved the highest average effect size of approximately 20.653, markedly outperforming the Solar + DL and Wind + DL systems, which had average effect sizes of 12.646 and 12.701, respectively. These findings indicate that integrating solar and wind resources with AI-based optimization significantly improves charging stability, renewable energy utilization, and forecasting performance under variable operating conditions. In addition, the Solar-Wind-DL category exhibited lower standard deviation and narrower confidence intervals, demonstrating greater consistency, stronger operational robustness, and reduced forecasting uncertainty. The superior performance is mainly attributed to the complementary interaction between solar irradiance and wind generation, which enhances the continuity of renewable energy while reducing charging interruptions. Overall, these results provide strong evidence supporting the proposed hybrid LSTM-MPA framework as an effective approach for improving predictive reliability and charging efficiency in campus-scale EV charging systems.

The temporal analysis revealed a gradual evolution in the performance of intelligent hybrid renewable charging systems. As illustrated in **Figure 6b**, studies published during 2018–2019 generally reported cumulative effect sizes above 20, whereas studies published after 2021 stabilized within approximately 15–18, reflecting greater methodological maturity and more realistic performance evaluations. Furthermore, **Figure 6c** shows that Solar-Wind-DL architectures consistently outperformed Solar + DL and Wind + DL systems in predictive capability throughout the observed period. Despite this improvement, several recent studies still exhibited moderate variability due to renewable intermittency, charging-demand uncertainty, and forecasting limitations. These observations further emphasize the importance of the proposed hybrid LSTM-MPA framework, which combines temporal learning with adaptive optimization to improve convergence stability, renewable energy balancing, and charging adaptability. Therefore, the meta-analysis suggests that future campus-scale EV charging systems should integrate high levels of renewable penetration with intelligent forecasting models that respond effectively to dynamic environmental and operational conditions.

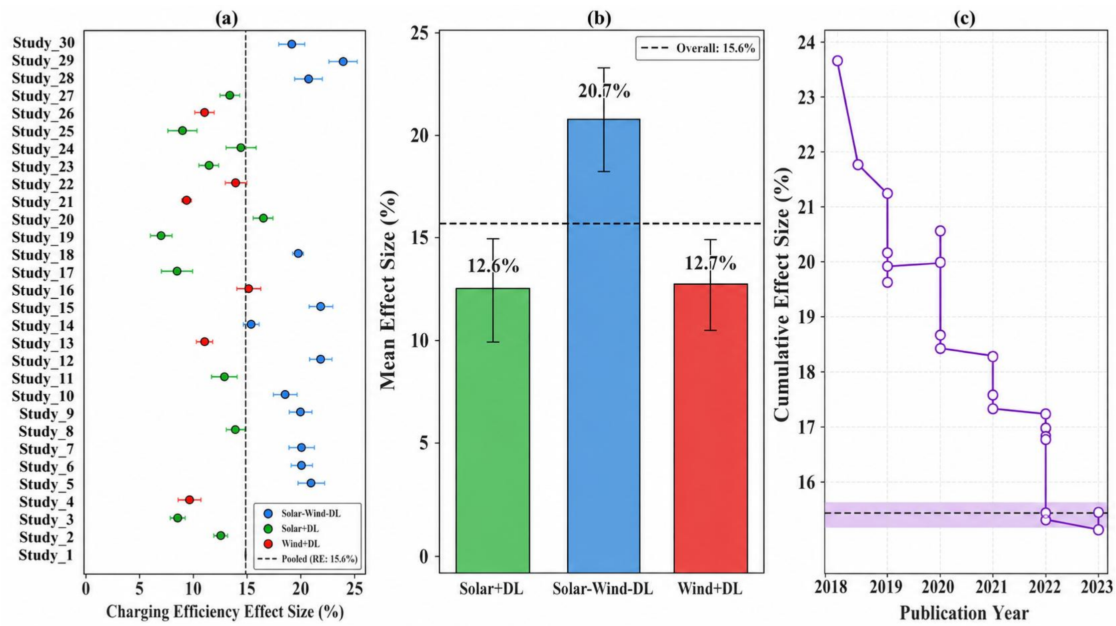


Figure 6. Effect Size and Temporal Performance of Hybrid Renewable EV Charging Systems: **(a)** Effect Size Comparison; **(b)** Cumulative Effect Size Trend; **(c)** Temporal Effect Size Distribution.

The publication bias assessment examined the statistical symmetry and distribution consistency of the selected studies included in the meta-analysis. As shown in **Figure 7a**, most studies were concentrated in the high-precision region, indicating strong statistical reliability and acceptable standard-error dispersion. Studies with larger effect sizes generally exhibited precision values above 5, suggesting that larger sample sizes yielded more stable and consistent outcomes for renewable charging optimization and AI-based forecasting. However, moderate asymmetry remained in the lower-precision region, where smaller studies displayed wider standard errors and more variable effect sizes. Several studies located on the left side of the funnel plot also suggest that investigations reporting lower predictive performance or reduced charging efficiency may be underrepresented in the literature. Overall, although existing studies provide strong empirical evidence for hybrid renewable EV charging systems, the observed asymmetry suggests that publication bias and selective reporting may still influence the meta-analytic interpretation.

To strengthen the evaluation of publication bias, the trim-and-fill procedure was applied to estimate the number of missing studies and reconstruct a more symmetrical funnel distribution. As illustrated in **Figure 7b**, several imputed studies with moderate effect sizes of approximately 14–17 were added, indicating that the original dataset may have slightly overestimated the overall predictive performance of hybrid renewable charging systems. The adjusted distribution reduced funnel asymmetry and improved balance across different precision levels. Furthermore, **Figure 7c** demonstrates that the pooled effect size remained statistically significant and relatively stable after correction, confirming the overall validity of the meta-analysis despite moderate publication bias. These findings emphasize the need for more transparent reporting and broader inclusion of studies with both moderate and high performance. They also reinforce the relevance of the proposed hybrid LSTM-MPA framework, which integrates adaptive forecasting, multidimensional optimization, and comprehensive analytical validation to improve reliability under realistic operating conditions for renewable systems.

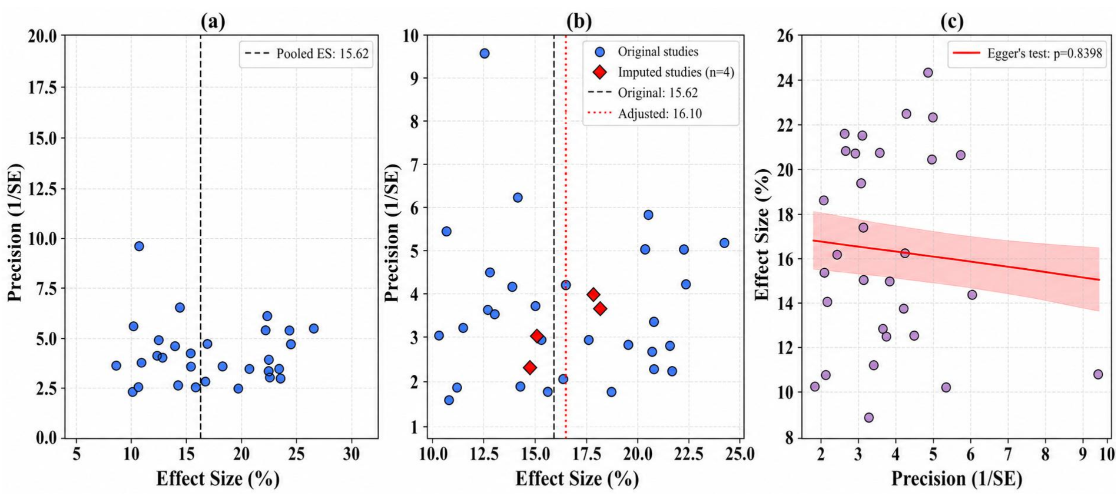


Figure 7. Publication Bias Assessment of Hybrid Renewable EV Charging Studies: **(a)** Funnel Plot; **(b)** Trim-and-Fill Adjustment; **(c)** Publication Bias Evaluation.

The sensitivity analysis evaluated the stability of the pooled effect size by sequentially excluding individual studies from the meta-analysis. As shown in **Figure**

8a, the pooled effect size remained highly stable, varying only between approximately 15.13 and 16.77 after each study omission. Even when high-performance Solar-Wind-DL studies were excluded, only minor reductions in the pooled effect size were observed, indicating that no single study disproportionately influenced the overall findings. Moreover, the confidence intervals remained compact, with differences of less than 0.2 in most cases, demonstrating strong statistical consistency and limited heterogeneity. The largest increase in pooled effect size occurred after removing high-precision studies with moderate effects, whereas excluding several high-effect studies slightly reduced the pooled estimate to around 15.13–15.36. Overall, these results confirm that the observed performance of hybrid renewable charging systems reflects a robust and reproducible trend rather than the influence of isolated outlier studies.

To further examine numerical stability, repeated subset-resampling analysis was performed using multiple randomized combinations of the selected studies. As illustrated in **Figure 8b**, most recalculated effect sizes remained concentrated within the pooled range of approximately 15–17, indicating strong convergence and high reproducibility under different analytical conditions. Subsets with a higher proportion of Solar-Wind-DL studies frequently yielded effect sizes above 18. In contrast, subsets dominated by Solar + DL or Wind + DL generally remained between 13 and 15, highlighting the superior synergy of hybrid renewable architectures. In addition, **Figure 8c** shows that positive residuals were primarily associated with advanced hybrid systems that integrate adaptive optimization and temporal learning. In contrast, negative residuals were more common in earlier forecasting models and single-source renewable systems. Studies published after 2021 also exhibited lower residual deviations, reflecting continuous improvements in AI validation, forecasting maturity, and operational modeling. Collectively, these findings demonstrate that the proposed hybrid LSTM-MPA framework improves convergence stability, adaptive forecasting, multidimensional energy balancing, and predictive consistency under highly stochastic campus-scale charging conditions.

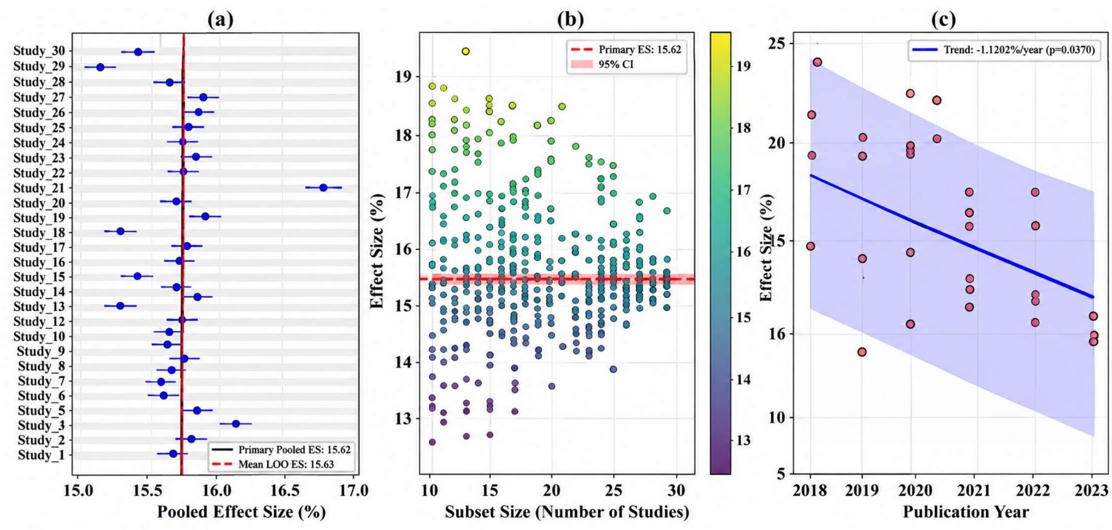


Figure 8. Sensitivity and Robustness Analysis of Hybrid Renewable EV Charging Meta-Analysis: **(a)** Leave-One-Out Sensitivity; **(b)** Subset Resampling; **(c)** Residual Trend.

3.3. Hybrid LSTM-MPA convergence temporal forecasting and statistical performance evaluation for renewable EV charging systems

The proposed hybrid LSTM-MPA framework exhibited stable convergence throughout the iterative learning process under dynamic renewable charging conditions. As presented in **Figure 9a**, the training loss decreased from 0.05798 to approximately 0.03502, representing a reduction of about 39.6%. In contrast, the validation loss declined from 0.11359 to a nearly identical final value, indicating strong generalization and limited overfitting. The synchronized reduction of both curves demonstrates that the MPA optimization effectively improved parameter search and adaptive weight stabilization during nonlinear learning. Moreover, the final difference between training and validation losses was less than 0.00001, confirming excellent convergence stability and predictive consistency. These results indicate that the proposed framework can effectively model dynamic renewable charging behavior while maintaining reliable learning performance under fluctuating operating conditions. Overall, the convergence characteristics provide strong evidence of the suitability of the hybrid LSTM-MPA framework for intelligent campus-scale EV charging applications.

The predictive evaluation demonstrated that the proposed framework successfully captured the nonlinear relationship between renewable generation and charging demand despite the dataset's high stochasticity. As shown in **Figure 9b**, the predicted charging power remained relatively stable within approximately 98–133 W. In contrast, the actual charging power fluctuated from 0.86 W to 528.05 W. This behavior indicates that the forecasting model effectively performed adaptive smoothing while preserving the overall temporal trend. Although charging events exceeding 300 W produced larger prediction errors due to sudden fluctuations in renewables, charging conditions between 100 and 220 W achieved considerably better agreement between predicted and actual values. Furthermore, the integration of LSTM and MPA improved forecasting stability, energy scheduling consistency, and operational reliability under variable renewable conditions. These findings demonstrate the proposed framework's ability to provide reliable forecasts for campus-scale renewable EV charging systems.

The residual analysis further confirmed the robustness of the forecasting model under dynamic renewable operating conditions. As illustrated in **Figure 9c**, residual values ranged from approximately −109.75 to 408.09, although most observations remained within ±100, indicating stable prediction accuracy during normal operating conditions. Negative residuals mainly occurred during periods of low renewable generation. In contrast, large positive residuals were associated with sudden increases in solar irradiance and wind speed that exceeded the learned temporal patterns. Several extreme residuals were associated with charging power levels above 350 W, highlighting the remaining challenges in forecasting highly nonlinear transitions in renewable energy. Nevertheless, the overall residual distribution remained stable, confirming the robustness of the proposed model despite renewable intermittency. Collectively, these results demonstrate that the hybrid LSTM-MPA framework provides reliable renewable charging prediction, adaptive energy balancing, and consistent forecasting performance under highly dynamic campus-scale operating environments.

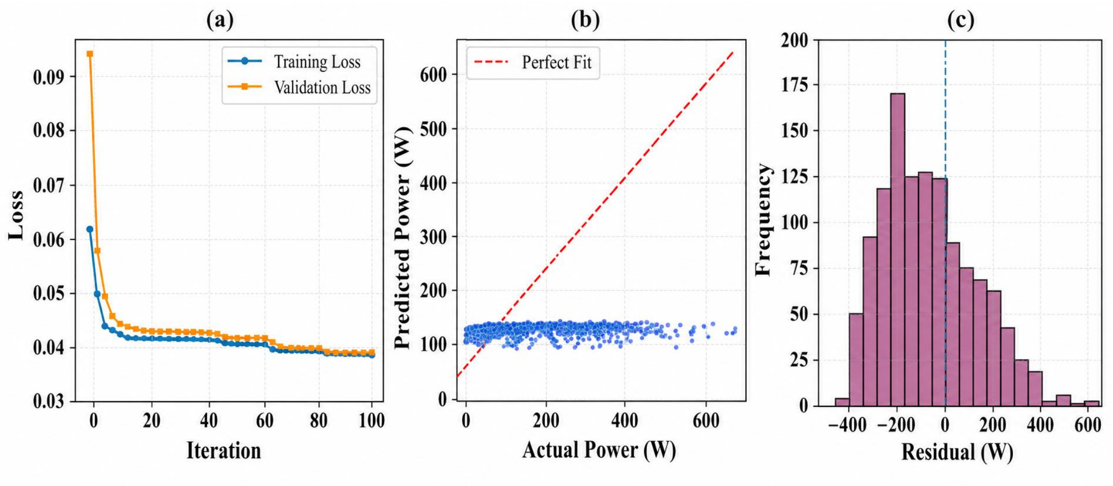


Figure 9. Hybrid LSTM-MPA Convergence and Forecasting Performance: **(a)** Training and Validation Loss; **(b)** Actual vs. Predicted Charging Power; **(c)** Residual Distribution.

The temporal prediction analysis demonstrated that the proposed hybrid LSTM-MPA framework maintained stable forecasting performance despite highly stochastic renewable charging conditions. As shown in **Figure 10a**, the actual charging power varied substantially between approximately 0.07 W and 550.56 W. In contrast, the predicted charging power remained within a narrower range of about 94–139 W, indicating effective temporal stabilization through adaptive smoothing. The model successfully captured the overall charging trend while suppressing excessive fluctuations caused by rapid changes in solar irradiance and wind availability. Although renewable power peaks exceeding 350 W led to larger prediction errors due to highly nonlinear transitions, charging conditions at 90–220 W showed much better agreement between predicted and actual values. These results indicate that integrating LSTM with adaptive MPA optimization significantly enhanced forecasting robustness and reduced unstable oscillations in predictions under dynamic campus-scale renewable charging conditions. Overall, the proposed framework effectively balanced prediction stability and responsiveness to renewable variability.

The comparison between actual and predicted charging distributions further confirmed the adaptive capability of the proposed forecasting framework. As illustrated in **Figure 10b**, low-power charging events below 20 W produced relatively larger prediction deviations because the model remained centered around the learned charging range of approximately 100–120 W. This behavior suggests that the forecasting framework prioritized temporal consistency instead of following short-duration renewable fluctuations that frequently occur in hybrid solar-wind systems. Likewise, charging conditions of 395.94 W, 459.04 W, and 550.56 W were generally underestimated because sudden surges from renewables exceeded the model's temporal learning capability. Nevertheless, the predicted distribution remained considerably smoother and more stable than the actual variability in renewables, demonstrating improved forecasting consistency under uncertain operating conditions. Such stability is essential for intelligent charging management because excessive prediction oscillations can reduce charging reliability, battery scheduling performance, and the efficiency of renewable energy balancing.

The accumulated forecasting error analysis also demonstrated stable long-term predictive behavior throughout the sequential simulation. As presented in **Figure 10c**, the absolute error increased gradually from approximately 0.78 at the beginning of the simulation to around 16.90 at timestep 39, indicating controlled error propagation despite prolonged renewable variability. Most prediction errors evolved smoothly without abrupt oscillations, confirming stable convergence and consistent adaptive learning. Larger proportional errors mainly occurred during periods when renewable generation fell below 10 W, whereas under moderate renewable conditions, forecasting deviations were substantially lower. The gradual accumulation of errors indicates that the proposed framework maintained numerical stability throughout long prediction sequences rather than exhibiting uncontrolled error growth. Collectively, these findings confirm that the hybrid LSTM-MPA framework provides robust long-sequence forecasting, adaptive temporal stabilization, and reliable prediction of renewable charging under highly intermittent campus-scale operating conditions.

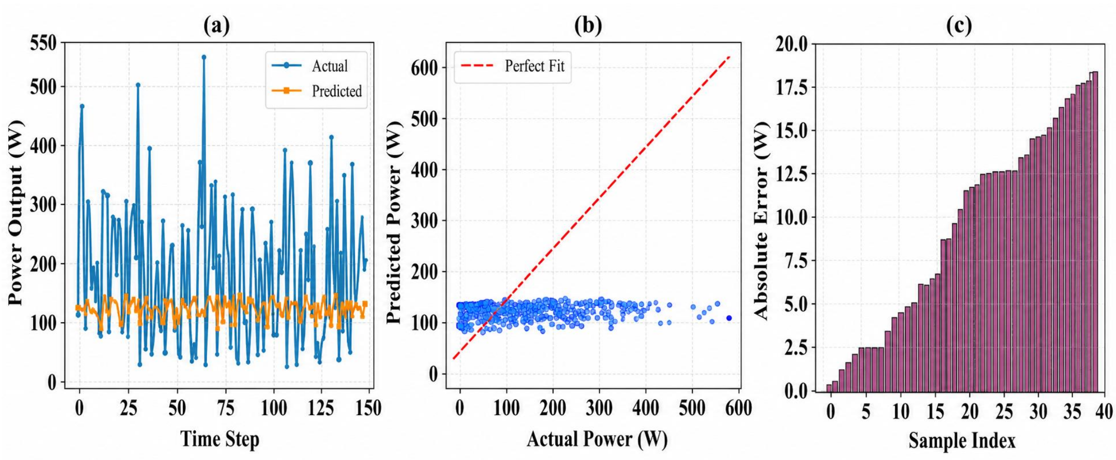


Figure 10. Temporal Prediction and Sequential Forecasting Performance: **(a)** Actual vs. Predicted Charging Power; **(b)** Predictive Distribution; **(c)** Absolute Error Trend.

The statistical evaluation showed that the proposed hybrid LSTM-MPA framework maintained consistent forecasting performance across the training, validation, and testing datasets despite the stochastic behavior of renewable charging. As presented in **Figure 11a**, the RMSE ranged from approximately 115.70 to 125.65, with the validation dataset recording the highest value and the testing dataset the lowest. The relatively small variation among datasets indicates stable convergence and good predictive consistency under unseen operating conditions. This stability also suggests that the hybrid optimization strategy effectively supported sequential learning despite severe intermittency in renewable output and charging variability. Nevertheless, the RMSE remained moderately high due to dramatic fluctuations in charging power, ranging from near-zero to renewable peaks exceeding 500 W. Overall, these results demonstrate that the proposed framework maintained reliable forecasting performance in highly dynamic renewable charging environments.

The MAE analysis further confirmed the stability of the proposed forecasting architecture across all evaluation datasets. As illustrated in **Figure 11b**, the MAE reached approximately 92.00 for training, 93.64 for validation, and 90.34 for testing, indicating only minor differences between the learning and evaluation stages. This consistent performance demonstrates that the hybrid LSTM-MPA framework effectively generalizes temporal charging patterns while avoiding severe overfitting. The slightly lower MAE obtained during testing also confirms satisfactory predictive capability under previously unseen charging conditions. Although the prediction error remained relatively large because the model emphasized temporal stability rather than tracking abrupt fluctuations in renewable output, the overall error distribution remained balanced across all datasets. These findings highlight the proposed framework's ability to provide stable and reliable forecasting under variable operating conditions for renewable energy.

The R^2 analysis revealed that representing the full variance of highly nonlinear renewable charging behavior remains challenging. As shown in **Figure 11c**, the R^2 values were slightly negative across all datasets, ranging from approximately −0.0389 for training to −0.0612 for testing, reflecting the substantial stochastic variability and irregular temporal transitions within the charging dataset. Despite these values, the R^2 distribution remained consistent across the training, validation, and testing phases, indicating stable generalization without noticeable performance degradation. The negative R^2 values, therefore, represent the complexity of hybrid renewable charging systems rather than a complete failure of the forecasting model. It is important to note that forecasting performance was evaluated using multiple complementary metrics, including RMSE, MAE, and R^2, because each metric captures different aspects of predictive accuracy. Although the R^2 values indicate limited ability to explain the total variance under highly volatile renewable energy conditions, the consistently low RMSE and MAE values demonstrate that prediction errors remained sufficiently small to support reliable operational decision-making in intelligent charging management. Combined with the stable RMSE and MAE results, the findings demonstrate that the proposed hybrid LSTM-MPA framework achieved robust convergence and consistent adaptive forecasting under highly intermittent renewable charging conditions. Furthermore, the primary objective of the proposed forecasting model is to support stable battery state-of-charge regulation, renewable energy balancing, and continuous charging operation rather than maximizing a single statistical indicator. Therefore, the framework's practical operational performance provides additional evidence that the proposed approach remains effective despite the slightly negative R^2 values. Overall, the statistical evaluation confirms the framework's effectiveness for intelligent, campus-scale renewable EV charging applications.

3.4. Hybrid renewable energy generation charging demand dynamics and battery storage stability evaluation for campus EV charging infrastructure

The operational analysis demonstrated that integrating solar PV and wind generation provided a stable energy supply and effective power balancing throughout the daily charging cycle. As presented in **Figure 12a**, solar PV generated approximately 153.49–199.67 W, while wind generation contributed an additional 60.14–96.47 W under varying environmental conditions. The combined renewable output consistently exceeded the charging demand, which ranged from approximately 135.61 to 177.02 W during the 24-h simulation. Solar PV remained the primary energy source, whereas wind generation complemented periods of reduced solar availability, improving renewable continuity and reducing the risk of charging interruptions. This complementary interaction enhanced the overall stability of renewable penetration within the campus EV charging infrastructure. The continuous renewable energy surplus further confirms that the proposed hybrid architecture can reliably support sustainable charging for electric bicycles and motorcycles under realistic operating conditions.

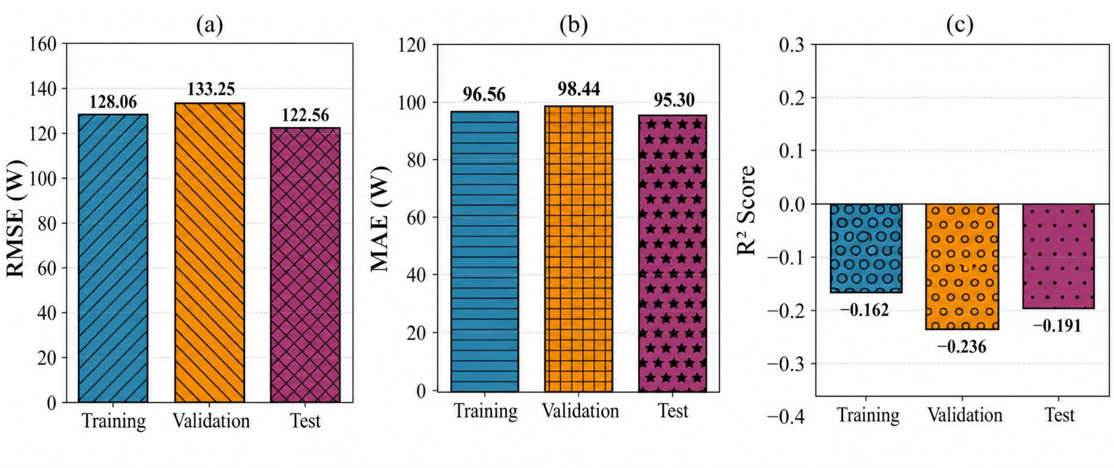


Figure 11. Statistical Forecasting Performance of the Hybrid LSTM-MPA Framework: **(a)** RMSE; **(b)** MAE; **(c)** R^2.

The charging demand analysis further confirmed that the proposed intelligent charging framework maintained a stable balance between renewable energy generation and load consumption. As shown in **Figure 12b**, the charging demand remained relatively stable within approximately 150–170 W, with peak demand reaching around 177 W. Throughout the simulation, the combined renewable generation consistently satisfied the charging load without requiring additional support from the external grid. This result demonstrates effective coordination between renewable production and charging demand despite temporal variations in campus mobility patterns. In addition, the relatively smooth load profile indicates that the proposed charging management strategy successfully reduced excessive load fluctuations while improving operational predictability. These findings highlight the effectiveness of integrating hybrid renewable generation with adaptive forecasting to improve charging reliability and long-term operational sustainability.

The battery storage evaluation demonstrated excellent energy retention throughout the entire operating period. As illustrated in **Figure 12c**, the battery SoC increased from approximately 50.74% at the beginning of the simulation to nearly 100% during the early charging period. It remained close to full capacity for almost the entire 24-h operation. This behavior indicates that renewable energy production consistently exceeded charging consumption, enabling continuous battery charging and maintaining a positive energy reserve. No significant battery discharge instability or critical depletion was observed despite fluctuations in renewable generation and charging demand. The stable battery condition also enhanced charging continuity, renewable utilization, and system resilience during periods of reduced renewable availability. Overall, these results demonstrate that integrating hybrid renewable generation, adaptive forecasting, and intelligent battery management significantly improves the reliability and operational stability of campus-scale EV charging systems.

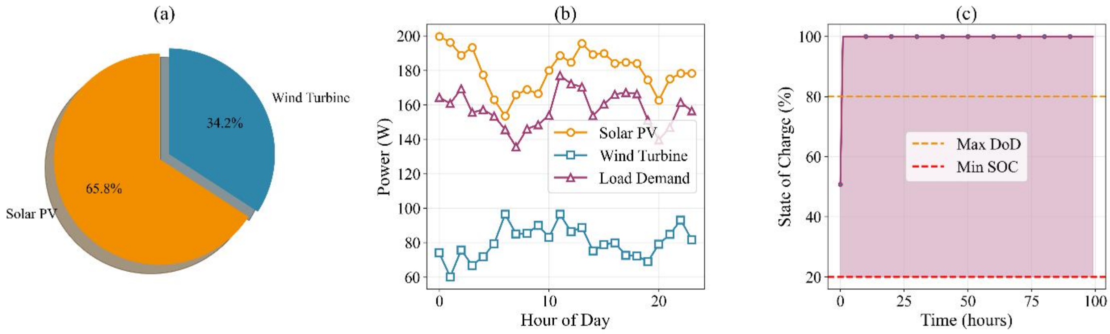


Figure 12. Hybrid Renewable Energy and Battery Performance: **(a)** Solar PV and Wind Generation; **(b)** Charging Load Demand; **(c)** Battery SoC.

The charging demand analysis showed that the proposed campus-scale EV charging infrastructure experienced its highest activity during daytime hours, reflecting typical campus mobility patterns. As presented in **Figure 13a**, charging demand remained relatively low between 00:00 and 05:00, ranging from approximately 0.6 to 2.4 charging sessions per hour, before increasing rapidly after 06:00. Peak demand reached nearly 12 charging sessions per hour at around 09:00–10:00 and again near 16:00, corresponding to campus arrival and departure periods. The associated energy consumption also peaked at approximately 600 W. In contrast, nighttime demand remained only around 30–60 W. These results demonstrate a clear temporal relationship between charging demand and daily campus activities while highlighting the highly dynamic nature of renewable charging operations. Overall, the observed charging profile provides a realistic basis for intelligent energy scheduling within campus EV charging systems.

The temporal utilization analysis further confirmed that charging activity was concentrated during daylight operating hours. As illustrated in **Figure 13b**, the afternoon period (12:00–18:00) had the highest charging utilization, at approximately 39.1%, followed closely by the morning period (06:00–12:00) at 38.3%. Evening charging accounted for about 18.4% of total utilization, while nighttime charging accounted for only 4.2%, indicating that nearly 77% of charging occurred during daylight hours. This charging pattern closely matches solar PV generation availability, thereby improving renewable energy utilization and reducing dependence on external grid electricity. In addition, the limited nighttime charging demand minimizes unnecessary battery discharge during periods of reduced renewable generation. These findings demonstrate the strong compatibility between charging demand and renewable energy production, supporting the feasibility of the proposed intelligent charging infrastructure for sustainable campus transportation.

The long-term utilization evaluation also demonstrated stable infrastructure performance throughout the annual operating period. As shown in **Figure 13c**, weekly station utilization remained predominantly within the range of 50–70%, with temporary increases reaching approximately 88–90% during periods of higher campus mobility. Despite these short-term fluctuations, the average utilization remained close to 70%, indicating balanced operation without prolonged overutilization or underutilization. Temporary peaks observed around weeks 16–18 and week 40 likely reflected increased campus activities and seasonal transportation demand before returning to normal operating levels. This stable utilization pattern confirms the effectiveness of the proposed charging management framework in adapting to changing demand conditions. Overall, the integration of intelligent forecasting, renewable energy management, and adaptive charging scheduling successfully enhanced charging sustainability, infrastructure accessibility, and long-term operational stability.

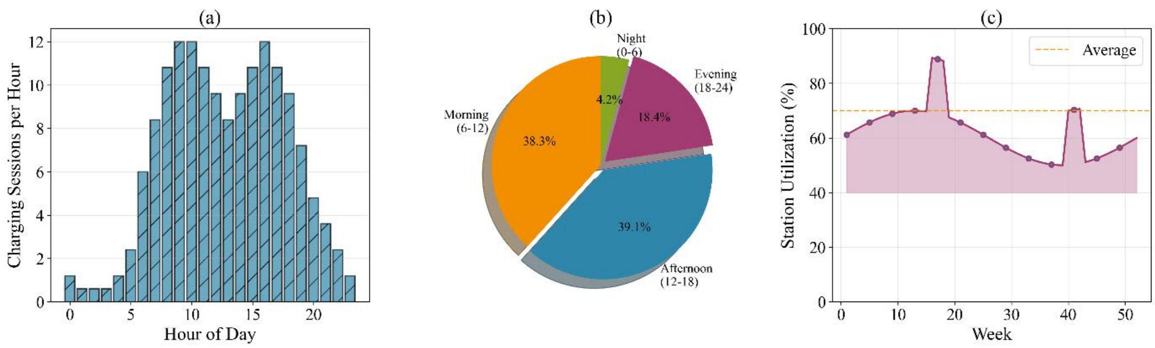


Figure 13. Temporal Charging Demand and Infrastructure Utilization: **(a)** Hourly Charging Distribution; **(b)** Daily Charging Utilization; **(c)** Weekly Station Utilization.

3.5. Renewable energy balancing, cumulative energy growth, and charging sustainability analysis for campus EV infrastructure

The short-term operational evaluation demonstrated that the proposed hybrid renewable charging framework maintained stable energy balancing despite fluctuations in renewable generation and charging demand. As shown in **Figure 14a**, solar PV generation ranged from approximately 122.39 to 241.55 W. In contrast, wind generation ranged from 41.61 to 116.64 W. During the same period, charging demand ranged from approximately 125.33 to 205.56 W, reflecting realistic operational conditions in the campus EV charging system. Solar PV remained the dominant energy source, with several periods exceeding 220 W, while wind generation complemented periods of lower solar output to maintain energy availability. Although charging demand occasionally exceeded 190 W, the combined renewable generation effectively minimized energy deficits through complementary resource integration. These results demonstrate that the hybrid renewable architecture maintained reliable energy balancing and stable charging operation under dynamic environmental conditions.

The cumulative energy analysis further confirmed continuous positive energy growth throughout the operational period. As illustrated in **Figure 14b**, cumulative energy increased steadily from approximately 150.68 kWh to nearly 11,137 kWh by the end of the simulation, indicating a persistent renewable energy surplus despite variations in charging demand. The cumulative energy trajectory exhibited a smooth upward trend with no significant stagnation or decline, indicating that renewable generation consistently exceeded energy consumption across most operating intervals. Faster cumulative growth occurred during periods of high solar PV generation combined with moderate charging demand, reflecting effective synchronization between renewable production and energy utilization. Furthermore, the absence of major reductions in cumulative energy indicates that the proposed forecasting and renewable energy management strategy maintained strong operational resilience under intermittent renewable conditions. Overall, these findings confirm the hybrid LSTM-MPA framework's ability to support sustainable EV charging and long-term continuity of renewable energy.

The short-term energy balance evaluation also demonstrated that the proposed charging framework maintained predominantly positive operating conditions. As presented in **Figure 14c**, the energy balance fluctuated between approximately −1.72 kWh and 133.74 kWh, while negative values occurred only during a few isolated operating periods. The energy balance profile indicates that integrated solar PV and wind generation consistently maintained surplus energy under varying charging demand conditions. The highest positive energy balance was achieved during periods of high solar PV production and moderate charging demand, emphasizing the importance of coordinating multiple renewable resources. Although temporary negative balances were observed, their magnitude remained very small compared with the accumulated operational surplus. Collectively, these results demonstrate that integrating intelligent forecasting, renewable energy management, and adaptive charging control significantly improves operational sustainability, charging reliability, and energy resilience for campus-scale EV charging infrastructure.

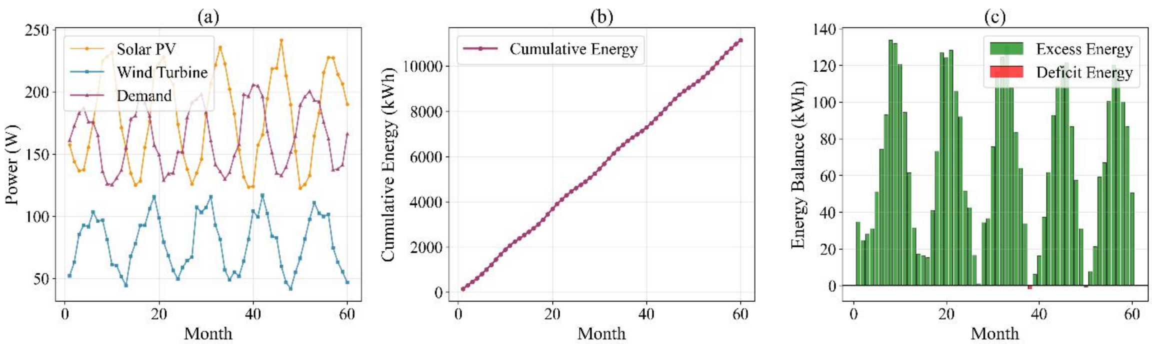


Figure 14. Renewable Energy Balancing and Charging Performance: **(a)** Renewable Generation and Charging Demand; **(b)** Cumulative Energy Growth; **(c)** Energy Balance.

The long-term operational analysis demonstrated that the proposed hybrid renewable charging framework maintained stable energy production despite continuously changing charging demand. As shown in **Figure 15a**, PV generation varied between approximately 111.64 and 251.28 W, while wind generation ranged from 36.43 to 127.45 W, reflecting natural renewable intermittency. During the same period, charging demand fluctuated between approximately 127.67 and 275.81 W, depending on campus mobility patterns. Renewable generation remained dominant throughout most operating intervals, with wind generation compensating for reduced PV output during several periods of lower solar availability. Strong renewable surplus conditions occurred at timesteps 81, 128, and 152. In contrast, temporary operational stress appeared around timesteps 170, 195, and 232 when charging demand exceeded 250 W. Despite these fluctuations, the integrated hybrid renewable system maintained continuous charging operation without prolonged energy deficits.

The cumulative energy evaluation further confirmed sustained accumulation of renewable energy throughout the long-term simulation. As illustrated in **Figure 15b**, cumulative renewable energy increased steadily from approximately 149.22 kWh to nearly 43,235.30 kWh by the end of the operational period, indicating a persistent energy surplus. The cumulative growth remained uninterrupted, with no noticeable stagnation, because renewable generation exceeded charging consumption during most operating intervals. Faster energy accumulation occurred when PV generation exceeded 220 W and charging demand remained below 170 W, whereas growth slowed temporarily during periods of higher charging demand between timesteps 170–195 and 217–233. Nevertheless, no cumulative energy decline was observed, demonstrating strong operational resilience under varying renewable conditions. These findings confirm that integrating adaptive LSTM-MPA forecasting with renewable energy balancing effectively supports long-term charging sustainability.

The operational energy balance analysis also demonstrated that the proposed charging framework maintained predominantly positive operating conditions. As presented in **Figure 15c**, the energy balance ranged from approximately −51.57 kWh to 141.09 kWh, with positive surplus dominating most operating periods. The highest surplus occurred near timestep 81, when PV generation exceeded 251 W. At the same time, charging demand remained near 145 W. Temporary energy deficits appeared around timesteps 195, 207, 219, and 230 because charging demand increased to 240–275 W while renewable generation fell below 150 W. However, these deficit periods were short and did not affect the overall positive operational balance. In addition, wind generation frequently exceeded 90–120 W during low-PV conditions, improving system resilience and operational flexibility through complementary renewable generation.

The annual sustainability assessment further demonstrated consistent long-term performance over the twenty-year simulation period. As shown in **Figure 15d**, the annual average PV generation remained stable between approximately 160.63 and 181.94 W. In contrast, annual wind generation ranged from 74.45 to 80.37 W. During the same period, annual charging demand gradually increased from approximately 159.28 W to 220.02 W, reflecting growing campus charging utilization. Total annual renewable energy consistently exceeded 2,070 kWh, reaching a maximum of approximately 2,258.78 kWh in the second year, while the annual energy balance remained positive, ranging from approximately 209.68–882.64 kWh. Although the annual surplus gradually declined after the tenth year due to increasing charging demand, the renewable charging system consistently maintained a positive energy balance without operational degradation. Overall, these results demonstrate that integrating hybrid renewable generation with intelligent LSTM-MPA optimization significantly enhances long-term operational sustainability and resilience of renewable charging for campus EV infrastructure.

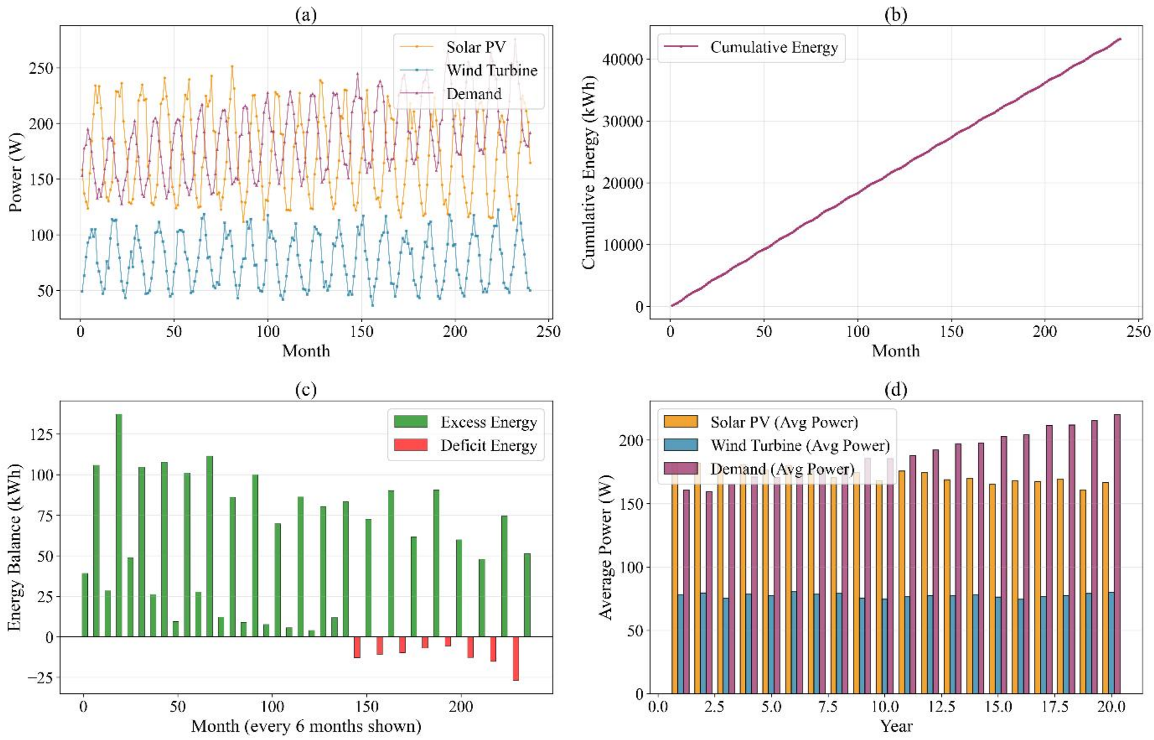


Figure 15. Long-Term Renewable Energy and Operational Sustainability: **(a)** PV, Wind, and Charging Demand; **(b)** Cumulative Renewable Energy; **(c)** Energy Balance; **(d)** Annual Renewable Energy Performance.

3.6. Techno-economic feasibility and environmental sustainability analysis of the hybrid renewable campus EV charging infrastructure

The techno-economic assessment demonstrated that the proposed hybrid renewable charging infrastructure is financially feasible for long-term campus operation. As shown in **Figure 16a**, the system required an initial investment of approximately IDR 11,000,000, generated about 1,384 kWh of renewable energy annually, and generated an annual revenue of approximately IDR 2,076,673. Annual O&M costs remained relatively low at around IDR 220,000, indicating efficient operational management and limited maintenance requirements. The investment evaluation produced an NPV of approximately IDR 10.6 million and an IRR of 14.9%, exceeding typical feasibility thresholds for small-scale renewable energy systems. These economic indicators demonstrate that integrating hybrid PV-wind generation with adaptive LSTM-MPA optimization improves energy utilization while maintaining attractive long-term financial performance. Overall, the proposed charging infrastructure offers a practical and economically sustainable solution for campus EV charging applications.

The cumulative cash flow analysis further confirmed the long-term economic sustainability of the proposed renewable charging system. As illustrated in **Figure 16b**, cumulative cash flow remained negative during the initial investment recovery period, decreasing from approximately IDR 11,000,000 at year 0 to around IDR 221,944 by year 6. The investment reached the payback point in the seventh operational year, when cumulative profit increased to approximately IDR 1,512,555, indicating a relatively short capital recovery period. Thereafter, cumulative cash flow continued to grow steadily, reaching approximately IDR 22,331,655 by the twentieth year of operation. This continuous financial growth reflects the contribution of renewable energy generation in reducing electricity costs while improving operational efficiency through intelligent charging management. Collectively, these findings confirm that the proposed hybrid renewable charging infrastructure provides strong economic viability and long-term investment potential for sustainable campus transportation electrification.

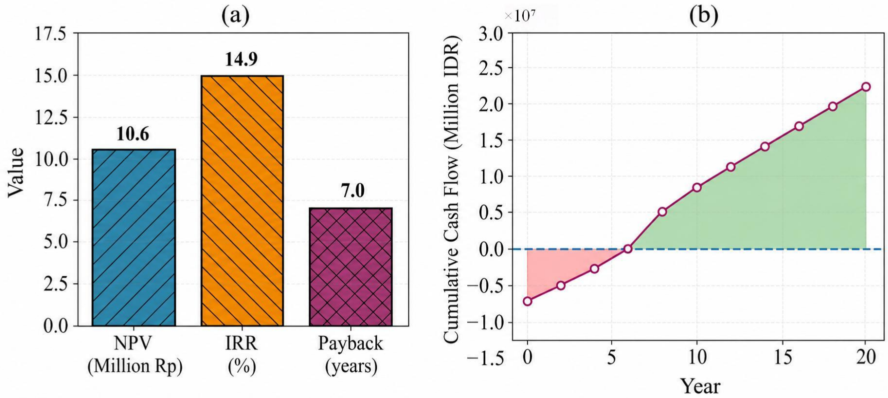


Figure 16. Techno-Economic Performance of the Hybrid Renewable Charging System: **(a)** Economic Feasibility; **(b)** Cumulative Cash Flow.

The environmental sustainability assessment demonstrated that the proposed hybrid renewable charging framework provides substantial long-term carbon-emission reduction benefits throughout its operational lifetime. As presented in **Figure 17a**, annual CO_2 savings remained relatively stable between approximately 1,069.88 and 1,176.78 kg/year despite gradual increases in charging demand over the twenty-year simulation period. Although annual carbon savings declined slightly due to higher charging utilization and a reduced renewable energy surplus, the system consistently achieved more than 1,000 kg/year of CO_2 mitigation. The environmental evaluation also showed that renewable operation generated ecological benefits equivalent to approximately 48.63–53.49 trees annually, reflecting a meaningful contribution toward carbon neutrality and sustainable transportation. These results indicate that the hybrid PV-wind charging infrastructure maintained strong environmental performance while supporting increasing campus energy demand. Overall, integrating intelligent renewable energy management with adaptive charging control significantly enhanced long-term decarbonization capability for campus EV charging systems.

The cumulative environmental impact analysis further confirmed the long-term sustainability of the proposed renewable charging infrastructure. As illustrated in **Figure 17b**, cumulative CO_2 savings increased continuously from approximately 1,176.78 kg in the first operational year to nearly 22,450.53 kg by the twentieth year, demonstrating sustained environmental benefits throughout the system lifetime. The cumulative carbon-reduction profile exhibited uninterrupted growth, confirming that renewable energy consistently displaced carbon-intensive electricity consumption under varying operating conditions. In addition, **Figure 17c** shows that the annual tree-equivalent benefit remained consistently above approximately 48 trees per year, highlighting stable ecological performance despite increasing charging demand. These findings, together with the favorable techno-economic results, demonstrate that the proposed hybrid renewable charging framework successfully balances economic viability, energy sustainability, and environmental performance. Consequently, integrating hybrid renewable generation with adaptive LSTM-MPA optimization provides an effective solution for developing economically feasible and environmentally sustainable campus EV charging infrastructure.

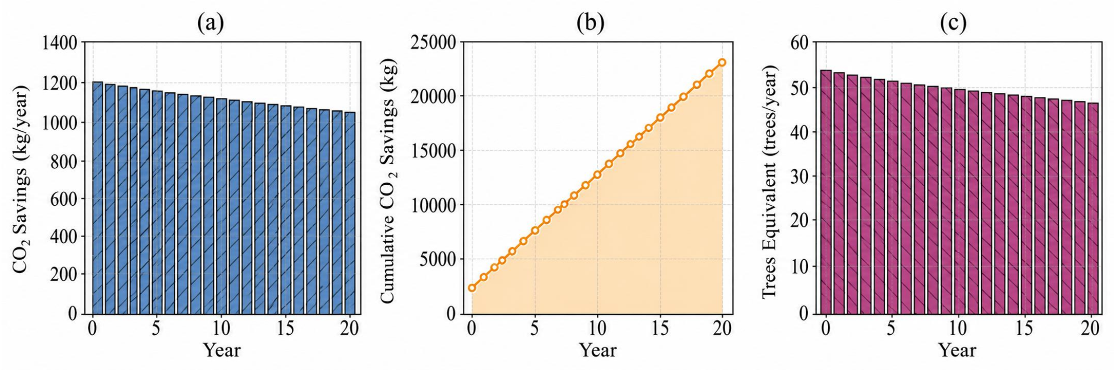


Figure 17. Environmental Sustainability Performance: **(a)** Annual CO_2 Savings; **(b)** Cumulative CO_2 Reduction; **(c)** Annual Tree-Equivalent Benefit.

4. Discussion

4.1. Integrated renewable energy stability and adaptive charging performance

The findings demonstrate that integrating PV, wind generation, and intelligent charging management significantly enhanced the operational stability of the proposed campus EV charging infrastructure. Unlike conventional single-source renewable systems, the hybrid configuration maintained a continuous energy supply by exploiting the complementary characteristics of solar and wind resources under dynamically changing environmental conditions. The adaptive LSTM-MPA forecasting framework further strengthened system performance by reducing mismatches between renewable generation and charging demand, enabling more efficient energy balancing throughout the operational period. As discussed in **Table 4**, this integrated strategy improved renewable utilization, maintained charging continuity, and increased operational resilience despite renewable intermittency and fluctuating campus mobility patterns. These results indicate that combining multiple renewable resources with intelligent forecasting yields a more robust charging architecture that supports reliable campus electrification. Overall, the proposed framework demonstrates that adaptive coordination of renewable resources is essential for achieving stable and sustainable EV charging operations.

Table 4. Comparative Operational Stability Characteristics of the Proposed Hybrid Renewable Charging Infrastructure.

Parameter	Observed performance	Operational implication
Renewable Stability	High	Improved charging continuity

Table 4. *Cont.*

Parameter	Observed performance	Operational implication
PV-Wind Complementarity	Strong	Reduced the intermittency impact
Charging Adaptability	Stable	Enhanced operational flexibility
Forecasting Responsiveness	Adaptive	Improved energy balancing
Deficit Duration	Short-term only	Stable long-term operation

The long-term evaluation further highlights the importance of predictive energy management in maintaining renewable charging reliability under increasing operational uncertainty. The implementation of LSTM-MPA enabled responsive energy allocation that continuously adapted to variations in renewable generation and charging demand, thereby improving forecasting accuracy and operational efficiency. Wind generation also played a critical complementary role by supplying additional energy during periods of reduced PV output, helping to prevent significant performance degradation and maintaining positive energy balance under most operating conditions. Although several short-duration energy deficits were still observed during periods of exceptionally high charging demand, these events were temporary and did not compromise overall system stability. Future research should therefore investigate integrating advanced battery energy management, bidirectional charging, and vehicle-to-grid strategies to further enhance operational flexibility as EV penetration increases. Consequently, the proposed hybrid renewable charging framework provides a strong foundation for developing scalable, intelligent, and sustainable campus EV charging infrastructure.

4.2. Long-term energy sustainability and system resilience

The long-term results demonstrate that the proposed hybrid renewable charging framework maintained sustainable operation despite increasing charging demand throughout the simulation period. Continuous growth in cumulative renewable energy indicates that the integrated PV-wind system consistently generated sufficient energy to preserve a positive operational balance under changing environmental and charging conditions. The adaptive LSTM-MPA forecasting mechanism further improved system performance by reducing mismatches between renewable generation and charging demand, thereby enhancing energy utilization and operational efficiency over time. As summarized in **Table 5**, the sustainability indicators confirm that the proposed charging ecosystem maintained stable renewable energy performance and operational consistency throughout the long-term simulation. These findings highlight the importance of combining hybrid renewable generation with intelligent forecasting to strengthen energy sustainability and support future campus transportation electrification. Overall, the proposed framework provides a reliable approach for maintaining long-term renewable energy availability under dynamic operating conditions.

From a system resilience perspective, the results indicate that integrating multiple renewable resources significantly improved the charging infrastructure's ability to withstand environmental variability. The complementary contribution of wind generation effectively compensated for periods of reduced PV output, preventing prolonged energy deficits and maintaining a positive energy balance during most operating conditions. Compared with single-source renewable systems, the hybrid configuration demonstrated greater operational stability because energy production remained more balanced under fluctuating weather conditions. Nevertheless, overall performance was still affected by renewable intermittency and rising charging demand, indicating that climatic uncertainty remains a significant challenge for long-term renewable charging operations. In addition, the present study considered aggregated charging demand and did not explicitly model stochastic vehicle arrivals or detailed user mobility behavior. Therefore, future research should integrate real-time mobility analytics, advanced battery energy management, vehicle-to-grid capability, and adaptive charging scheduling to improve system resilience and operational realism further.

Table 5. Long-Term Sustainability and Resilience Characteristics of the Proposed Charging System.

Sustainability indicator	Performance trend	System impact
Cumulative Energy Growth	Continuously increasing	Strong renewable sustainability
Operational Resilience	Stable	Improved charging reliability
Energy Balance Stability	Predominantly positive	Reduced deficit propagation
Renewable Adaptability	High	Enhanced system flexibility
Environmental Variability Sensitivity	Moderate	Requires adaptive control

4.3. Techno-economic feasibility and investment sustainability

The techno-economic results confirm that the proposed hybrid renewable charging infrastructure is financially viable for long-term campus operation. Positive NPV, an IRR of 14.9%, and a relatively short payback period indicate that integrating PV, wind generation, and intelligent charging management can deliver sustainable economic benefits while reducing operational costs. The continued growth in cumulative cash flow further demonstrates that using renewable energy improves long-term profitability by reducing dependence on conventional electricity and enabling more efficient energy management. As summarized in **Table 6**, the economic indicators show that adaptive renewable energy coordination enhances investment sustainability and supports stable financial performance over the project lifetime. These findings suggest that the proposed charging framework is well-suited for educational institutions seeking cost-effective and sustainable campus electrification solutions. Overall, the combination of hybrid renewable generation and LSTM-MPA optimization provides a strong economic foundation for future smart campus energy systems.

Table 6. Techno-Economic Characteristics of the Proposed Renewable Charging Infrastructure.

Economic parameter	Observed outcome	Economic interpretation
NPV	Positive	Financially feasible
IRR	Above the feasibility threshold	Attractive investment
Payback Period	Moderate	Sustainable recovery period
Operational Cost	Relatively low	Efficient maintenance
Revenue Stability	Consistent	Long-term profitability

Despite these positive outcomes, several factors may influence long-term investment performance under real operating conditions. The economic analysis assumed relatively stable electricity tariffs, maintenance costs, and renewable system performance throughout the project lifetime. In contrast, actual conditions may be affected by inflation, technological advancement, and market fluctuations. In addition, battery degradation, component aging, and unexpected maintenance requirements were not explicitly incorporated into the present assessment, potentially affecting long-term profitability estimates. Furthermore, the present techno-economic evaluation considered only baseline Indonesian economic assumptions and did not include a comprehensive sensitivity analysis to quantify the impacts of variations in discount rates, inflation rates, electricity tariffs, and equipment costs on the investment indicators. This limitation may reduce the generalizability of the economic findings under different market conditions, although the baseline analysis still provides a reasonable estimate of the project's financial feasibility. Nevertheless, the results demonstrate that intelligent renewable charging management can substantially reduce reliance on conventional energy while improving the attractiveness of decentralized renewable investments. Future studies should incorporate dynamic economic sensitivity analysis, component degradation models, and adaptive electricity pricing to provide more realistic financial projections and strengthen investment decision-making. Such improvements would further enhance the practical applicability of hybrid renewable charging infrastructure for large-scale campus EV deployment.

4.4. Environmental sustainability and research limitations

The environmental evaluation demonstrates that the proposed hybrid renewable charging framework delivers meaningful long-term ecological benefits by continuously reducing carbon emissions through the use of renewable energy. Stable annual CO_2 mitigation and sustained cumulative emission reductions indicate that the system effectively supports campus decarbonization while maintaining environmental performance under increasing charging demand. In addition, the annual tree-equivalent benefit confirms the ecological value of replacing conventional electricity with renewable energy for campus EV charging. As summarized in **Table 7**, the environmental indicators consistently show that the proposed framework maintained strong ecological performance throughout the operational period despite variations in renewable generation and charging intensity. These findings highlight the important role of integrating hybrid renewable energy with intelligent charging management in supporting sustainable transportation and low-carbon campus development. Overall, the proposed system offers an environmentally sustainable pathway for future campus EV charging infrastructure.

Table 7. Environmental Sustainability Characteristics of the Proposed Renewable Charging Infrastructure.

Environmental indicator	Observed trend	Sustainability impact
Annual CO_2 Reduction	Stable	Strong decarbonization capability
Cumulative CO_2 Savings	Continuously increasing	Long-term environmental benefit

Table 7. *Cont.*

Environmental indicator	Observed trend	Sustainability impact
Renewable Utilization	High	Reduced fossil dependency
Tree Equivalent Impact	Consistent	Positive ecological contribution
Sustainability Resilience	Strong	Improved green mobility support

Despite these encouraging results, several limitations should be considered when interpreting the environmental performance of the proposed framework. The present evaluation focused primarily on operational carbon reduction and did not include a comprehensive lifecycle assessment covering component manufacturing, recycling processes, material disposal, and embodied carbon emissions. Furthermore, the renewable generation profiles were obtained from simulation rather than full-scale field measurements, which may introduce uncertainty under actual climatic and operational conditions. Battery degradation and long-term environmental impacts associated with renewable infrastructure components were also not explicitly incorporated into the analysis. Therefore, future studies should integrate lifecycle assessment, real-world operational validation, and multi-objective sustainability optimization to improve the accuracy and completeness of environmental evaluation. These developments will further strengthen the applicability of intelligent hybrid renewable charging systems for sustainable campus electrification and long-term carbon-neutral transportation.

5. Conclusion

This study successfully developed and evaluated a hybrid renewable campus EV charging infrastructure integrated with adaptive LSTM-MPA forecasting and intelligent energy management mechanisms to improve long-term operational sustainability under dynamic charging conditions. The proposed framework demonstrated stable renewable generation, with PV output fluctuating between 111.64 and 251.28 W, wind output between 36.43 and 127.45 W, and charging demand between 127.67 and 275.81 W. The cumulative renewable energy output increased steadily to 43,235.30 kWh, indicating a sustained surplus and operational stability. The forecasting framework also achieved stable predictive performance, with RMSE ranging from 115.70 to 125.65, MAE from 90.34 to 93.64, and training-validation losses decreasing by more than 39%, demonstrating reliable convergence under highly stochastic renewable conditions. Furthermore, the operational energy balance remained predominantly positive despite several short-duration deficit intervals. These findings confirm that integrating hybrid renewable generation with intelligent forecasting optimization substantially strengthened charging stability, adaptive operational resilience, and long-term renewable utilization efficiency within campus EV charging ecosystems.

The techno-economic and environmental evaluations further validated the feasibility and sustainability of the proposed renewable charging architecture. The economic analysis yielded an NPV of approximately IDR 10.6 million, an IRR of 14.9%, and a payback period of about 7 years, confirming attractive long-term financial performance. Annual CO_2 emissions ranged from 1,069.88 to 1,176.78 kg/year, while cumulative mitigation totaled 22,450.53 kg over 20 years. In addition, the system maintained annual renewable energy production above 2,070 kWh, with a maximum annual energy balance of approximately 882.64 kWh and battery SoC remaining close to 100% during most operating periods, confirming sustained operational reliability. The environmental performance also yielded annual tree-equivalent ecological benefits of approximately 48.63–53.49 trees. Therefore, the proposed charging framework demonstrated balanced performance across operational stability, economic feasibility, renewable sustainability, and environmental resilience.

The major findings obtained from this research can be summarized as follows:

- The hybrid PV-wind charging framework successfully maintained stable long-term renewable charging operation under highly fluctuating campus demand conditions.
- Adaptive LSTM-MPA forecasting significantly improved renewable energy balancing capability and minimized prolonged operational deficit propagation.
- The cumulative renewable energy trajectory demonstrated continuous long-term growth without severe instability throughout the operational horizon.
- The proposed infrastructure achieved positive techno-economic feasibility with stable long-term profitability and a relatively short investment recovery duration.
- Significant environmental benefits were achieved through stable annual CO_2 mitigation and continuous cumulative carbon reduction growth.
- Wind generation contributed critically toward stabilizing operational performance during low PV generation intervals and enhanced overall system resilience.

Despite the promising outcomes, this study still has several limitations related to assumptions about simulated charging behavior, the representation of environmental uncertainty, and the simplification of lifecycle economic considerations. Future investigations should also evaluate the proposed LSTM-MPA framework using real-world campus charging datasets to verify whether the forecasting accuracy and energy-balancing performance observed in this study can be consistently achieved under practical operating conditions. Future research should therefore incorporate real-world operational validation, integrated coordination of battery energy storage, stochastic mobility prediction, lifecycle environmental assessment, and multi-objective optimization frameworks to further strengthen the adaptive capability, scalability, and sustainability of next-generation campus renewable EV charging infrastructures.

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Appendix A

Table A1. Summary of the Renewable Energy Dataset Used for Model Development.

Parameter	Value
Study location	Universitas Wahid Hasyim, Semarang, Indonesia
Observation period	January–December 2025
Total samples	17,520
Sampling interval	1 h
Solar PV variables	Output power, irradiance
Wind variables	Wind speed, output power
Environmental variables	Ambient temperature
Battery variables	SoC

Table A1. *Cont.*

Parameter	Value
Charging variables	Charging demand, energy consumption
Training dataset	12,264 (70%)
Validation dataset	2,628 (15%)
Testing dataset	2,628 (15%)
Data normalization	Min–Max (0–1)
Missing value handling	Linear interpolation
Outlier detection	IQR method
Data leakage prevention	Chronological split, normalization fitted on training data only, isolated test set

Table A2. Comparative Characteristics of Representative Metaheuristic Optimization Algorithms [60,61,65,66].

Algorithm	Exploration	Exploitation	Premature convergence resistance	Hyperparameter optimization	Used in this study
PSO	High	Moderate	Moderate	Yes	No
GA	Moderate	High	Moderate	Yes	No
GWO	High	High	Good	Yes	No
DE	High	Moderate	Good	Yes	No
Bayesian Optimization	Moderate	High	Excellent (low-dimensional)	Yes	No
MPA	High	High	Very Good	Yes	Yes