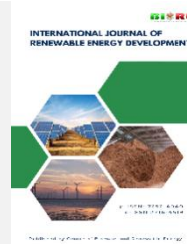




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Research Article

Enhance EV station charge and discharge based on deep learning forecasting method incorporating renewable energy sources and multi-objective optimization algorithm

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Abstract. As electric vehicle charging station operations become more common, proper coordination of energy management is necessary to avoid high operational costs and carbon emissions caused by electric vehicle charging requirements, intermittent renewable sources, and fluctuating electricity rates. In this research, a forecast-based optimization methodology is created with the objective of optimizing the charge-discharge management of a renewable-powered electric vehicle charging station system involving photovoltaic generation, wind generation, fuel cells, electric vehicles, and stationary batteries. First, a recurrent neural network is used to predict relevant time series data, such as photovoltaic energy, wind energy, electric vehicle load demand, fuel cell energy production, and electric vehicle energy consumption. These forecasted data are then applied to a bi-objective energy management optimization problem, which is solved using NSGA-II. The objective is to minimize operating cost and CO_2 emissions while considering power balance, grid energy exchange, and other operational constraints associated with the fuel cell, battery storage system, and electric vehicles. In this study, two scenarios are examined using one month of hourly data; Scenario 1 does not use stationary batteries, whereas Scenario 2 uses them. The forecasting results show robust predictions, with one-hour-ahead R^2 values ranging from 0.9162 to 0.9708. The optimization results show that Scenario 2 provides better energy shifting and peak-period support through battery charging and discharging management. Compared with Scenario 1, the operating cost is reduced from \$171,833.86 to \$160,388.44, and CO_2 emissions are decreased from 13,485.48 kg to 12,892.23 kg, leading to 6.7% and 4.4% reductions, respectively.

Keywords: Electric Vehicle Charging Stations (EVCS), Deep Learning (DL), Recurrent Neural Network (RNN), Renewable Energy Source (RES), Battery Energy Storage System, Vehicle to Grid.



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1. Introduction

Rapid development of Electric Vehicle (EV) technology, along with changing preferences toward Renewable Energy Sources (RES), has influenced the consumption and distribution of energy (Michaelides *et al.*, 2023; Sinha *et al.*, 2023). Increased use of electric vehicles across the globe has led to an increasing need for effective charging stations and consequently created the need for Electric Vehicle Charging Stations (EVCSs) (Bhosale *et al.*, 2024; Jalili Irani *et al.*, 2025; Mohammed *et al.*, 2024). However, managing electric vehicle charging stations remains challenging, especially where there are changes in the energy supply. Such challenges include increasing the efficiency of using renewable energy sources, reducing costs, and decreasing pollution (Gawusu *et al.*, 2022; Pei *et al.*, 2024).

The increasing deployment of EVCSs has motivated tighter integration of local renewables, such as solar and wind, into EVCS operation to enhance sustainability (Ahmad *et al.*, 2023; Taghizad-Tavana *et al.*, 2023). Battery Energy Storage Systems (BESS) and Vehicle-to-Grid (V2G) technology, in particular, can provide adjustable charge-discharge flexibility to balance supply and demand (Bhatti *et al.*, 2024). Efficient management of

these resources requires accurate forecasting approaches and reliable energy management systems that can address renewable intermittency and variable electricity prices while simultaneously minimizing grid reliance and peak demand (Senthil Kumar *et al.*, 2024). Several researchers have put forward various methodologies to optimize EVCS operations by coupling RES and energy storage technology, but difficulties in predicting demand and renewable power production remain, along with coordinating multi-energy dispatch under time-varying prices and operational constraints (Alharbi *et al.*, 2025). In addition, many scheduling methodologies for EVCSs still rely on conventional forecasting methods. The application of deep learning algorithms and deep reinforcement learning for microgrid energy management shows higher effectiveness in representing nonlinearities and uncertainties in scheduling problems (Sakib *et al.*, 2025; Shen *et al.*, 2024; Yu *et al.*, 2024). This knowledge can be applied to create scheduling frameworks where the operation of EVCSs with battery and V2G potential takes forecasting results into account. Several works have been devoted to recent advances in EVCS operations, planning, and forecasting.

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(Ozkan *et al.*, 2022) have introduced the Electric Vehicle Charging-Discharging Station Scheme, which integrates charging stations into commercial parking facilities to improve energy efficiency for the grid, EV operators, and drivers. Their strategy uses commercial enterprise loads and EVs as consumers, while photovoltaic-battery systems, EV discharging, and the utility grid act as energy suppliers. Simulations conducted at a shopping mall in Turkey have shown that the proposed scheme reduces daily energy consumption, peak power demand, and operator energy costs. (Baherifard *et al.*, 2022) have proposed a two-stage framework for planning commercial parking lot charging stations to address EV demand and grid imbalance. In the first stage, the profitability of EV charging programs is evaluated by considering battery parameters, transportation details, and EV sales, whereas the second stage assesses the impact of charging stations on network imbalance in an IEEE distribution system. Their results show a 23% increase in EV user profits and a 30% reduction in network imbalance without changing the distribution network structure. (Kim *et al.*, 2023) have presented a deep-learning-based forecasting framework for microgrid operation that accounts for uncertainties in RES generation, load, and day-ahead electricity prices by employing an LSTM model whose

hyperparameters are tuned through a hybrid GA–PSO scheme and enhanced by an attention mechanism. (Al-Dahabreh *et al.*, 2023) have proposed a data-driven system for assessing consumer-perceived quality of experience at public EV charging stations and used a machine-learning model trained on real-world data to estimate long-term EVCS loads and support smart infrastructure development. (Aduama *et al.*, 2023) have suggested a multi-feature data collection technique based on an LSTM model to improve EV charging station load forecasting. By incorporating meteorological variables such as wind speed, temperature, and humidity, the final model achieves a mean absolute prediction error of 3.29%, outperforming the initial LSTM model. (Aldossary *et al.*, 2024) have developed an energy forecasting method for EV charging stations that integrates solar and wind data into the Stem-Auxiliary-Reduction-LSTM-Dense Network model. Using 3.5 years of data from California, the proposed model outperforms LSTM, XGBoost, and ARIMA, with a MAPE of 7.2%, RMSE of 22.3 kWh, and an R^2 of 0.87. (Ghenai *et al.*, 2024) have developed ANN-based models for short-term prediction of photovoltaic power output and EV charging station battery condition, demonstrating the importance of predictive tools for solar-powered EVCSs. (Chengyu Yang *et al.*, 2024) designed an attention-enhanced

Table 1
Summary of studies.

Study	Model	Key Findings	Results	Year
(Ozkan <i>et al.</i> , 2022)	Electric vehicle charging-discharging station Scheme	Integrated charging stations into commercial parking facilities for energy efficiency	Decreased energy consumption, peak power demand by 32.86%, and operator costs by 36.70%	2022
(Baherifard <i>et al.</i> , 2022)	Two-stage framework for planning CPL charging stations	Profitability analysis of EV charging and its impact on network imbalance	23% increase in user profits, 30% reduction in network imbalance	2022
(Kim <i>et al.</i> , 2023)	LSTM + Global Attention with GA-PSO hyperparameter tuning	Improved microgrid forecasting accuracy uncertainty via attention-enhanced LSTM and meta-heuristic tuning	Lower forecasting errors (e.g., MAE/RMSE) than baseline predictors on historical data (PJM)	2023
(Al-Dahabreh <i>et al.</i> , 2023)	System for assessing QoE at public EV charging stations	Developed QoE indicators and used machine learning for load forecasting	Handled increasing demand while maintaining acceptable QoE levels	2023
(Aduama <i>et al.</i> , 2023)	LSTM-based multi-feature data collection for EV charging station load forecasts	Incorporated historical meteorological data to improve EV load forecasting	Mean absolute prediction error of 3.29%, outperforming initial LSTM model	2023
(Aldossary <i>et al.</i> , 2024)	SARLDNet model (LSTM-based) integrating solar and wind data	Enhanced accuracy by integrating temporal learning and feature selection techniques	MAPE of 7.2%, RMSE of 22.3 kWh, and R^2 score of 0.87, better than LSTM, XGBoost, and ARIMA	2024
(Ghenai <i>et al.</i> , 2024)	ANN-based models for short-term solar PV power output and EV battery condition predictions	Combined solar PV and smart meter data for predictive models	PV power R values from 0.9957 to 0.9969, battery charge values from 0.9990 to 0.9996	2024
(Chengyu Yang <i>et al.</i> , 2024)	Attention-SLSTM model for EV charging demand forecasting	Used attention mechanism for time-series forecasting	MAE of 1.6860, RMSE of 2.5040, MAPE of 9.768%, superior to LSTM and stacked-LSTM	2024
(Wang <i>et al.</i> , 2024)	LSTM + Bayesian Network) + demand response optimization	Combined uncertainty-aware deep learning forecasting with DR optimization to support more robust operational scheduling	Improved prediction performance and demonstrated operational benefit	2024
(Dai <i>et al.</i> , 2025)	Hybrid cointegration–BiLSTM framework for EV charging pile capacity prediction	Cointegration to identify correlations with socioeconomic variables	49% decrease in MAE, 26% decrease in RMSE, and 24% decrease in error compared to GRU baseline	2025
(Koca, 2025)	Hybrid energy system model for EV battery charging stations using DNN for load shedding	Maximized renewable energy use, optimized energy costs, and reduced grid load	Improved load shedding by 25%, system stability by 15%, and performance by 98%	2025
(Güven <i>et al.</i> , 2025)	HOMER Grid software optimization for renewable energy-powered EVCS	Optimization of grid-connected PVs, batteries, biodiesel generators, and EVCS components	Reduced CO2 emissions by 29.40%, unburned hydrocarbons by 96.16%, LCOE to \$0.0549/kWh, NPV of 1.62 million USD	2025

stacked LSTM architecture for station-level EV charging demand prediction and achieved better results than LSTM-based models. (Wang *et al.*, 2024) devised an LSTM-Bayesian network forecasting model to overcome the unpredictability of renewable power generation and incorporate their approach into a demand-response optimization framework. (Dai *et al.*, 2025) have introduced a combined cointegration Bi-LSTM technique to forecast the charging pile capacity of EVs and observe considerable declines in error margins when compared with previous techniques. (Koca, 2025) constructed a PV-wind energy generation system to charge EV batteries and deploys load shedding through a deep neural network, while (et al., 2025) evaluated the performance of renewable energy-based EV charging stations with the help of HOMER Grid.

A summarized overview of representative recent studies is provided in Table 1. In spite of these improvements, there are some deficiencies that should be addressed in the existing body of knowledge. Many models depend on classical optimization algorithms that may be inadequate for representing the stochastic and dynamic nature of renewable energy resources, and their application could adversely affect the efficiency and accuracy of energy management and forecasting. Although various studies have employed machine learning techniques, quite a few systems have yet to explore the full potential of deep learning for modeling the nonlinear relations between energy production, consumption, storage operations, and market dynamics. In addition, the integration of V2G has been insufficiently considered in the context of forecasting-to-operation paradigms based on deep learning technologies. Besides, the influence of price fluctuations and grid stress conditions is generally overlooked, resulting in limited effectiveness of scheduling policies for electric vehicle charging stations. Finally, there is an obvious need to develop a more holistic and flexible strategy for optimizing EV charge/discharge scheduling and minimizing operating costs and emissions.

This study intends to overcome these limitations through an innovative forecast-to-operation method for optimizing EVCS scheduling under the influence of diverse DERs. In this regard, the methodology of this study involves an effective forecasting algorithm based on recurrent neural networks, combined with a multi-objective optimization algorithm that considers PV, wind, and fuel cell power sources, as well as BESS and V2G vehicles, to manage operational flexibility. This problem is formulated and solved using NSGA-II with the objectives of reducing operating cost and CO₂ emissions, respecting system constraints, and performing scenario analysis to evaluate the scheduling policy. Therefore, the main goal of this study is to design and evaluate a deep learning-based energy management model for EVCSs that can improve charge-discharge scheduling, increase energy efficiency during peak hours, and strengthen the economic and environmental performance of EVCS operation under practical operating limitations.

2. Methodology

The methodology of the research involves the use of various RES, BESS, and V2G technologies in order to improve the efficiency of the EV charging and discharging process. DL techniques are applied using RNNs in order to predict energy production from solar, wind, and fuel cell sources, along with EV consumption needs and changes in battery energy storage. As a result, this allows the coordination of energy flows and decreases dependency on electricity grids and associated costs. Moreover, system adjustments are made according to changes

in renewable energy availability and electricity prices. In addition, using V2G technologies makes it possible for EVs to supply power to the grid during peak load times. For evaluation purposes, simulations are used with a focus on decreasing carbon emissions and operational costs, increasing renewable energy use, and improving system efficiency.

Fig. 1 illustrates the overall schematic of the proposed forecast-assisted EVCS energy management framework, including the main system components and the two studied scenarios.

2.1. Photovoltaic generation model

The efficacy of solar panels depends on multiple conditions, including solar irradiance, humidity, temperature, and battery charge level. The present study uses a precise mathematical scheme to compute the electrical output of solar panel assemblies, as illustrated in Eq. (1) (Chengying Yang *et al.*, 2024):

$$p_{pv}(t) = \eta_{pv} \times A_{pv} \times G(t) \quad (1)$$

Eq. (2) takes into account the rate of solar radiation ($G(t)$, KW/m^2), the area of the module (A_{pv} , m^2), and the total efficiency of the solar system η_{pv} , which was obtained from as follows:

$$\eta_{pv} = \eta_{pv} \times \eta_{rec} [1 - \beta(T_c(t) - T_{c,ref})] \quad (2)$$

Furthermore, the solar module efficacy η_{pv} matches the control unit's charge efficacy $\eta_{rec} = 1$, which is identical to the MPPT inverter-charging system. To compute the ambient temperature coefficient for a module that uses the baseline temperature $T_{c,ref}$ of solar cells as follows in Eq. (3):

$$T_c(t) = T_a(t) + \left(\frac{NOCT - 20}{800} \right) \times G_t \quad (3)$$

where $T_a(t)$ is the ambient temperature and $NOCT$ is the nominal operating cell temperature. Finally, the total PV output is computed as $P_{pv}(t) = N_{pv} \times p_{pv}(t)$ where N_{pv} is the count of PV modules.

2.2. Wind power generation model

Wind power depends on turbine characteristics and wind speed. The wind turbine power curve is modeled as (Sakki *et al.*, 2022):

$$\underline{p} = \begin{cases} 0 & x < x_{\min} \\ \eta(x)p_0(x) & x_{\min} \leq x < x_{\max} \\ I & x_{\max} \leq x < x_s \\ 0 & x \geq x_s \end{cases} \quad (4)$$

Here, $p_0(x)$ represents theoretical power, I represents nominal power, and $\eta(x)$ represents total efficacy, controlled by a stochastic process x . The RES's limits $x_{\min}$ and $x_{\max}$ are typical, whereas x_s is a safety cut-out number. Location, turbine design, and RE system specifics affect wind power generation. Therefore, this context defines wind power as:

$$p_0(\underline{v}) = \frac{1}{8} \rho_a \pi D^2 \underline{v}^3 \quad (5)$$

ρ_a denotes density of the air, D signifies the wind turbine's diameter and $\underline{v}$ signifies the wind speed.

2.3. Fuel cell model

The FC acts as a controllable source that compensates for shortfalls from wind and PV while supporting the load

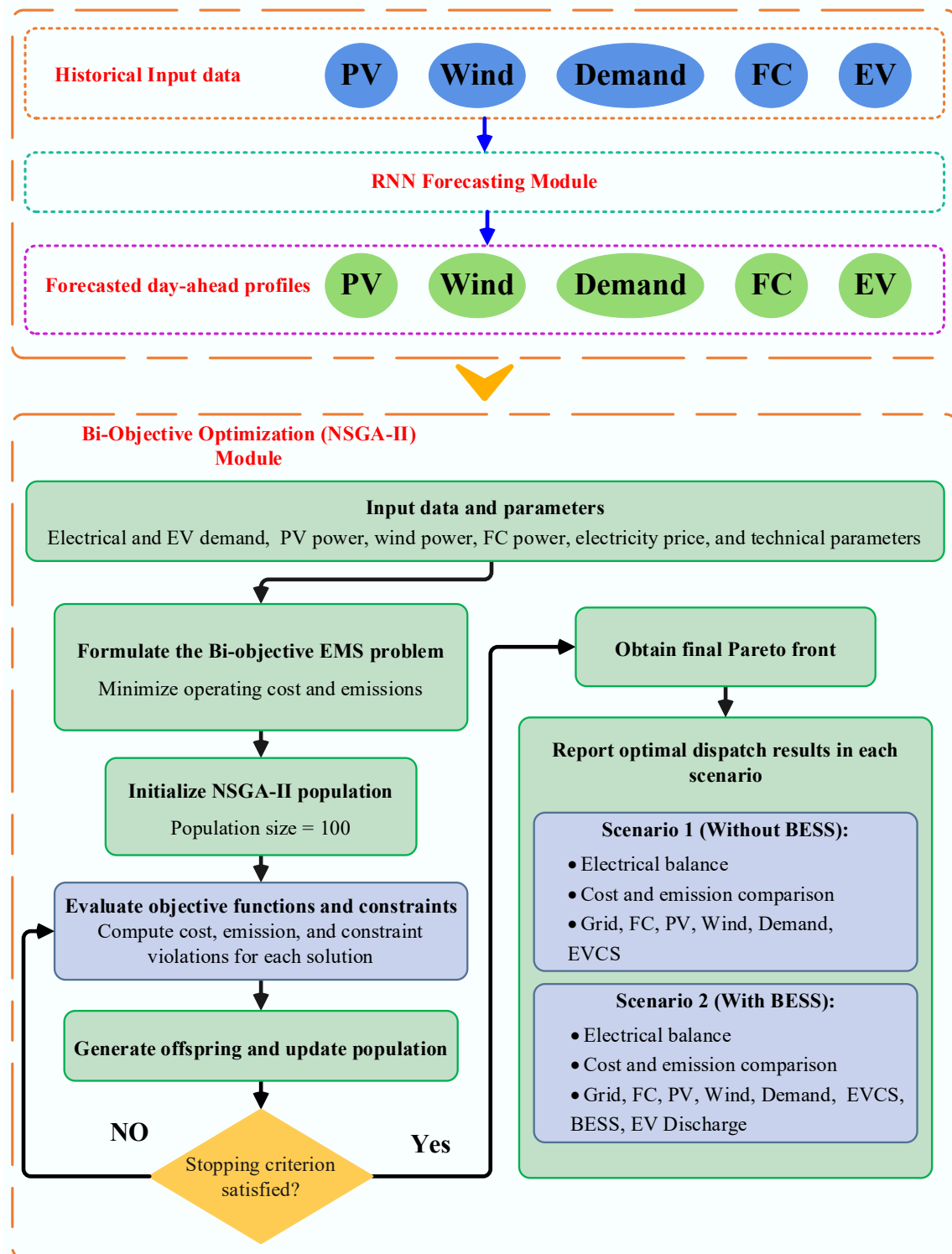


Fig. 1. Schematic diagram of the proposed forecast-assisted bi-objective energy management framework for Scenarios.

continuously. Hydrogen is stored upstream (electrolyzer), and electrochemical conversion inside the FC stack produces electrical power from the stored fuel. The instantaneous electrical output delivered to the inverter is modeled as

$$P_{FC-inv,t} = \eta_{FC} P_{FC,t} \quad (6)$$

where $P_{FC,t}$ is the gross stack power and $\eta_{FC} \in (0,1]$ is the FC efficiency, which includes inverter losses if not modeled

separately. To ensure feasible operation, the FC output is constrained within its rated limits:

$$P_{FC}^{\min} \leq P_{FC,t} \leq P_{FC}^{\max}, \forall t \quad (7)$$

FCs typically show limited dynamic response; therefore, the FC dispatch is constrained with ramp-up and ramp-down to prevent unrealistic fast variations. Assuming an hourly schedule resolution ($\Delta t = 1$ h), the constraint is defined as follows in Eq. (8):

$$-R_{FC}^{down} \leq P_{FC}(t) - P_{FC}(t-1) \leq R_{FC}^{up}, \quad \forall t = 2, \dots, T \quad (8)$$

where R_{FC}^{up} and R_{FC}^{down} (kW/h) denote the maximum ramp-up and ramp-down rates of the fuel cell, respectively. This constraint captures the FC's slow dynamics and ensures that rapid EV-induced fluctuations are mainly accommodated by BESS/V2G actions within their power and state-of-charge limits, while the FC supplies the smoother component of residual demand.

2.4. Battery energy storage system model

The constraints apply to the operation plan of BESS as follows in Eqs. (9-14) (Karimi *et al.*, 2023):

$$SoC_{m,t+1} = SoC_{m,t} + \Delta T \left(\frac{\eta_m^{Ch} P_{m,t}^{Ch}}{E_m} - \frac{P_{m,t}^{Dis}}{E_m \eta_m^{Disch}} \right) \quad (9)$$

$$SoC_m^{\min} \leq SoC_{m,t} \leq SoC_m^{\max} \quad (10)$$

$$0 \leq P_{m,t}^{Ch} \leq X_{m,t}^{Ch} P_m^{Ch,max} \quad (11)$$

$$0 \leq P_{m,t}^{Dis} \leq X_{m,t}^{Dis} P_m^{Dis,max} \quad (12)$$

$$X_{m,t}^{Ch} + X_{m,t}^{Dis} \leq 1 \quad (13)$$

$$SoC_{m,1} = SoC_{m,T} \quad (14)$$

The dynamic state of charge (SoC) for the BESS is delineated in Eq. (9). The permissible ranges for SoC, charging power, and discharging power are specified in Eqs. (10-12), respectively. Eq. (13) enforces mutual exclusivity, prevents simultaneous charge and discharge. Lastly, Eq. (14) states that the beginning and last stored energy in the BESS must be equivalent.

2.5. EV station model

The EVCS is modeled as an aggregated controllable unit that pools power from plugged EVs and (if present) the on-site BESS. Dispatch variable $P_{EVCS,t}$ (positive to grid, negative from grid) is limited by station hardware (Hafeez *et al.*, 2023):

$$P_{EVCS,t}^{\min} \leq P_{EVCS,t}(t) \leq P_{EVCS,t}^{\max} \quad (15)$$

The aggregated EV fleet power is shown in Eq. (16):

$$P_{EVCS}(t) = \sum_{n \in \mathcal{N}} (P_n^{dis}(t) - P_n^{ch}(t)) \quad (16)$$

Per-EV limits with availability $\delta_{n,t} \in \{0,1\}$, plugged-in indicators are as follows in Eq. (17) and Eq. (18):

$$0 \leq P_{n,t}^{ch} \leq \delta_{n,t} P_n^{ch,max} \quad (17)$$

$$0 \leq P_{n,t}^{dis} \leq \delta_{n,t} P_n^{dis,max} \quad (18)$$

2.6. Battery degradation cost model for V2G operation

Battery aging increases with additional V2G cycling; therefore, a degradation cost is incorporated using an energy-throughput approximation used in a V2G optimization study (Preis *et al.*, 2023). The degradation cost over the horizon is modeled as follows in Eq. (19):

$$C_{deg} = \sum_{t=1}^T c_{deg} P_{EV_{dch}}(t) \Delta t \quad (19)$$

where c_{deg} (\$/kWh) signifies the monetized battery wear per discharged kWh and Δt is the time-step duration. Reported values in (Preis *et al.*, 2023) are typically on the order of fractions of a cent per kWh, depending on battery condition and cycling assumptions.

2.7. Bi-objective optimization problem formulation

The energy management problem is established as a bi-objective enhancement that simultaneously lowers operating cost and total emissions over the horizon $t = 1, \dots, T$: $\min [f_1, f_2]$. The Pareto-optimal trade-off set between f_1 and f_2 is generated utilizing the Non-dominated Sorting Genetic Algorithm II. The optimization is subject to the system power-balance equation, grid exchange limits, fuel cell operating constraints, battery energy storage constraints, and EV charging/discharging constraints.

2.7.1. Operating cost objective function

For both studied scenarios, the first objective is defined as $f_1 = \text{Cost}_1$ as shown in Eq. (20), where a binary indicator σ_{BESS} is used to represent the availability of the stationary battery energy storage system, such that $\sigma_{BESS} = 0$ for Scenario S1 (without BESS) and $\sigma_{BESS} = 1$ for Scenario S2 (with BESS). Accordingly, the BESS-related term is activated only when the storage system is available:

$$f_1 = \sum_{t=1}^T \left(P_{grid}(t) \cdot \text{Cost}_{grid}(t) + P_{FC}(t) \cdot \text{Cost}_{FC} + P_{PV}(t) \cdot \text{Cost}_{PV} + P_{wind}(t) \cdot \text{Cost}_{wind} + \sigma_{BESS} (P_{BESS_{dch}}(t) - P_{BESS_{ch}}(t)) + P_{EV_{dch}}(t) - P_{EV_{ch}}(t) - P_{demand}(t) \right) \quad (20)$$

$P_{grid}(t)$ implies power purchased from the grid at time t and $\text{Price}(t)$ refers to the price of electricity at time t . $P_{FC}(t)$ represent the power generated by the fuel cell at time t . $P_{solar}(t)$ is the power generated by the solar system at time t , $P_{wind}(t)$ is the power generated by the wind system at time t , and $P_{BESS_{dch}}(t)$ denote the BESS charging and discharging powers, respectively. $P_{EV_{ch}}(t)$ denotes the power used for EV charging, $P_{demand}(t)$ imply the total residential and commercial demand at time step t . The objective is evaluated over $t = 1, \dots, T$ under the adopted sign and accounting conventions used consistently in the scenario-based analysis.

When V2G operation is enabled, the operating-cost objective includes the battery degradation cost as defined in Section 2.6. Therefore $f_1 = \text{Cost} + C_{deg}$. When V2G discharge is not activated ($P_{EV_{dch}}(t) = 0$), $C_{deg} = 0$ and f_1 reduces to the corresponding operating-cost expression.

2.7.2. Emission objective function

The second objective is defined as $f_2 = \text{Emission}$ as follows in Eq. (21) for both scenarios:

$$f_2 = \sum_{t=1}^T \left(E_{grid}(t) \cdot P_{grid}(t) - E_{EV}(t) \cdot P_{EV_{dch}}(t) - E_{BESS}(t) \cdot P_{BESS_{dch}}(t) \right) \quad (21)$$

Where $E_{\text{grid}}(t)$ refer to emission factor for the grid at time t (in units of kg CO₂/kWh), $P_{\text{grid}}(t)$ implies the power purchased from the grid at time t , $E_{\text{EV}}(t)$ is the emission factor for EV discharging, $P_{\text{EV_dch}}(t)$ signifies the power discharged from the EV back to the grid, $E_{\text{BESS}}(t)$ denotes the emission factor for battery discharging (if the battery is charged from the grid), and $P_{\text{BESS_dch}}(t)$ is power discharged from the battery into the grid.

Grid emissions are directly proportional to the power purchased from the grid. As the grid typically relies on fossil fuels, which produce CO₂ emissions. Both EV discharging and battery discharging help reduce emissions when they supply power to the grid, as they decrease reliance on grid power during high-emission periods. Therefore, these values are subtracted from the total emissions.

2.7.3. System power balance and grid exchange constraints

To ensure operational feasibility at every time step, the optimization is subject to the system power-balance equality and grid exchange limits. The power balance is enforced as follows in Eq. (22):

$$\begin{aligned} & (P_{\text{grid}}(t) + P_{\text{FC}}(t) + P_{\text{PV}}(t) + P_{\text{wind}}(t) \\ & + P_{(\text{BESS}_{\text{dch}})}(t) + P_{(\text{EV}_{\text{dch}})}(t)) \\ & = P_{\text{demand}}(t) + P_{(\text{EV}_{\text{ch}})}(t) \\ & + P_{(\text{BESS}_{\text{ch}})}(t), \quad \forall t \end{aligned} \quad (22)$$

where $P_{\text{demand}}(t)$ denotes the aggregated demand at time t . $P_{\text{EV}_{\text{ch}}}(t)$ and $P_{\text{EV}_{\text{dch}}}(t)$ signifies EV charge and V2G discharge powers, respectively, $P_{\text{BESS}_{\text{ch}}}(t)$ and $P_{\text{BESS}_{\text{dch}}}(t)$ implies the BESS charge and discharge powers. The grid power exchange is constrained by Eq. (23):

$$0 \leq P_{\text{grid}}(t) \leq P_{\text{grid}}^{\text{max}}, \quad \forall t. \quad (23)$$

The remaining component-level constraints, which include fuel-cell bounds, BESS SoC dynamics and limits with mutual exclusivity, and EV charging/discharging limits with availability, are enforced as defined in the subsections of the methodology.

2.8. Recurrent neural network forecasting model

An RNN-based forecaster has been used to identify temporal relationships in the multivariate time-series signals employed by the EMS for short-term prediction. Fig. 2 presents the unrolled RNN structure employed in the forecasting layer to learn temporal dependencies in the historical time-series data and generate day-ahead predictions for the optimization module.

Let $x_t \in \mathbb{R}^{d_x}$ represent the input at time t , $h_t \in \mathbb{R}^{d_h}$ denote the hidden state, and $\hat{y}_t \in \mathbb{R}^{d_y}$ signify the output. An RNN updates in the following manner as follows in Eq. (24) and Eq. (25) (Sheikhemari, 2022):

$$h_t = \phi(W_{xh}x_t + W_{hh}h_{t-1} + b_h), \quad (24)$$

$$\hat{y}_t = (W_{hy}h_t + b_y) \quad (25)$$

where W_{xh}, W_{hh}, W_{hy} are trainable weight matrices and b_h, b_y denotes biases. $\phi = \tanh(\cdot)$ is set with the following, as shown in Eq. (26):

$$\tanh(a) = \frac{e^a - e^{-a}}{e^a + e^{-a}} \quad (26)$$

Sequence mapping. Following Fig. 2, training samples are formed from sliding windows of W as follows in Eq. (27):

$$[x_{t-W+1}, \dots, x_t] \rightarrow [\hat{y}_{t+1}, \dots, \hat{y}_{t+H}] \quad (27)$$

Where H is the prediction horizon.

Conventional RNNs can produce vanishing-gradient effects for long-range dependence. Fixed-length windows (W) with a defined horizon (h) provide steady learning over the operating horizon. The RNN has been selected for its efficient and stable integration with the EMS, whereas LSTM/GRU (Fuseler *et al.*, 2022; Nhat *et al.*, 2023) and attention-oriented schemes are known alternatives that could be incorporated in the same forecasting-to-optimization workflow.

2.8.1. Training & Convergence (RNN)

The dataset is separated into train and test sets, with 80% allocated for training and 20% for testing. The schemes get training with training data and are subsequently evaluated on a testing set to measure their performance and generalization abilities. The speed and stability of the RNN's learning is assessed from the inputs (PV, Wind, Fuel-Cell, EV, Demand) using MSE as the exclusive loss metric, presents convergence curves (epoch vs. MSE), the early-stopped best epoch, and the final horizon-average MSE.

2.9. Forecast Evaluation metrics

Metrics calculate the horizon-average MSE and use it to assess predictions at each horizon step $h = 1, \dots, H$ as follows in Eq. (28) and the horizon-average MSE is defined in Eq. (29) (Islam *et al.*, 2022):

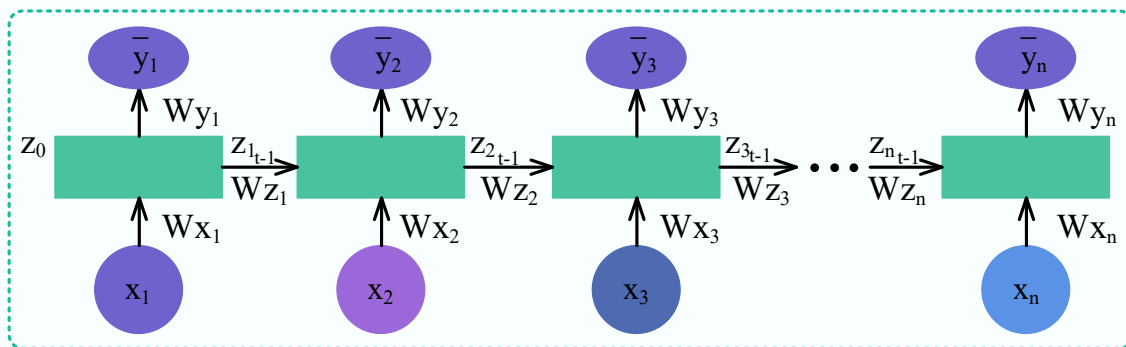


Fig. 2. Unrolled recurrent neural network structure used in the forecasting layer.

$$MSE_h = \frac{1}{N} \sum_{i=1}^N (y_{t+h}^{(i)} - \hat{y}_{t+h}^{(i)})^2, \quad (28)$$

$$\overline{MSE} = \frac{1}{H} \sum_{h=1}^H MSE_h \quad (29)$$

The following metrics, including MAE and RMSE, are used to score our predictions as follows in Eq. (30) and Eq (31) (Medina-Santana *et al.*, 2022):

$$MAE = \sum_{t=1}^H \frac{|A_t - F_t|}{H} \quad (30)$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^H (A_t - F_t)^2}{H}} \quad (31)$$

Here A denotes the observed value, F signifies the estimated value, H shows the forecast horizon.

The coefficient of determination is as follows in Eq. (32):

$$R^2 = 1 - \frac{\sum_{i=1}^N (y^{(i)} - \hat{y}^{(i)})^2}{\sum_{i=1}^N (y^{(i)} - \bar{y})^2} \quad (32)$$

where $y^{(i)}$ and $\hat{y}^{(i)}$ signifies the observed and predicted values, $\bar{y}$ signifies the mean of the observed values, N is the count of evaluated samples, and H denotes the forecast horizon.

Simulations have been carried out on a computer with a 7500 CPU (3.40 GHz) and 32 GB RAM. The multi-objective

energy management problem is solved via NSGA-II, which is implemented in the PYMOO framework. The scheme has been organized as a bi-objective optimization that optimizes both operational costs and total pollution emissions while conforming to an hourly power-balance constraint. For complete reproducibility, the solver configuration is clearly reported: NSGA-II is run with a population size of 100, and convergence is enforced by a fixed-generation termination condition of $n_{gen} = 1000$.

3. Simulation and numerical result

The simulation is conducted for 30 days (720 hours) using real historical data adapted from a publicly available microgrid dataset from (*Energy-Management-Systems-Using-Deep-Learning*, n.d.)

The dataset represents an hourly commercial-building demand profile together with renewable generation information, which makes it suitable for evaluating forecast-assisted energy management under realistic operating variability.

3.1. Input Profiles

Fig. 3 shows the daily curves of renewable energy availability and electricity price used in the scheduling process. Fig. 3(a) shows that the availability of solar energy is concentrated in daylight hours, while wind energy varies and is less predictable than solar energy because it does not always

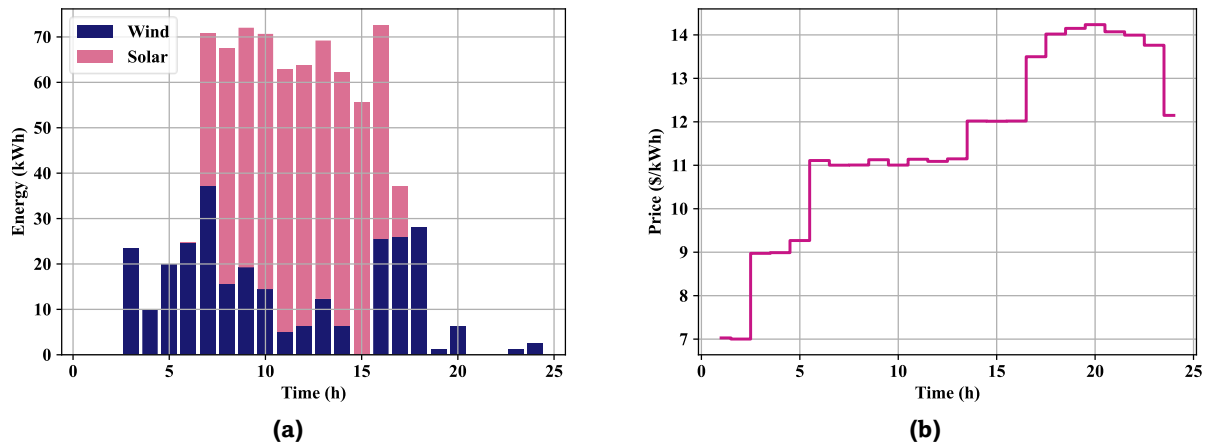


Fig. 3. Renewables and price inputs.

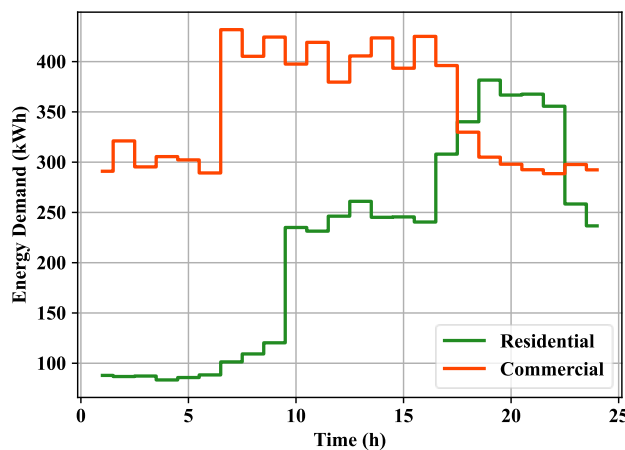


Fig. 4. Overall demand of the proposed system.

occur in fixed time slots. Therefore, there is no clear match between renewable energy availability and periods with relatively high electricity prices. In Fig. 3(b), electricity prices slowly increase during the day and reach their maximum value in the evening, when solar energy can no longer be harvested and contributions from wind energy are limited. The misalignment between renewable availability and higher electricity-price periods indicates the need to properly schedule EV charging, V2G discharging, and BESS charging and discharging. Thus, the daily curves shown in Fig. 3 provide the primary justification for moving energy consumption from high-price periods to periods with more renewable energy availability and lower electricity prices.

The demand profiles utilized within the EVCS scheduling problem are highlighted in Fig. 4. Regarding the commercial load, there is a relatively higher load during much of the operating period throughout the day, specifically between 07:00 and 17:00. On the other hand, residential demand starts at a low level and gradually increases until the evening, when there is a surge in load. It is evident from this analysis that the two loads possess different time-dependent features, resulting in uneven

load profiles throughout the scheduling period. The latter feature becomes crucial because the evening increase in demand occurs when solar power generation is unavailable and the price of electricity increases significantly. This demand behavior supports the need for coordinated EV charging, BESS operation, and V2G discharging to reduce grid dependence during high-demand and high-price periods.

3.2. Power predictions

The convergence behavior of the recurrent neural network forecasting models is presented in Fig. 5, where the MSE of predictions for PV output, wind power, demand, fuel cell output, and EV power is provided. In all time series, MSE rapidly declines at the beginning of training because the RNN models quickly learn the primary structure of the input data series. After the initial rapid drop in the error values, the plots show gradual leveling off, since additional training iterations contribute only marginally to performance improvement. All forecasting models

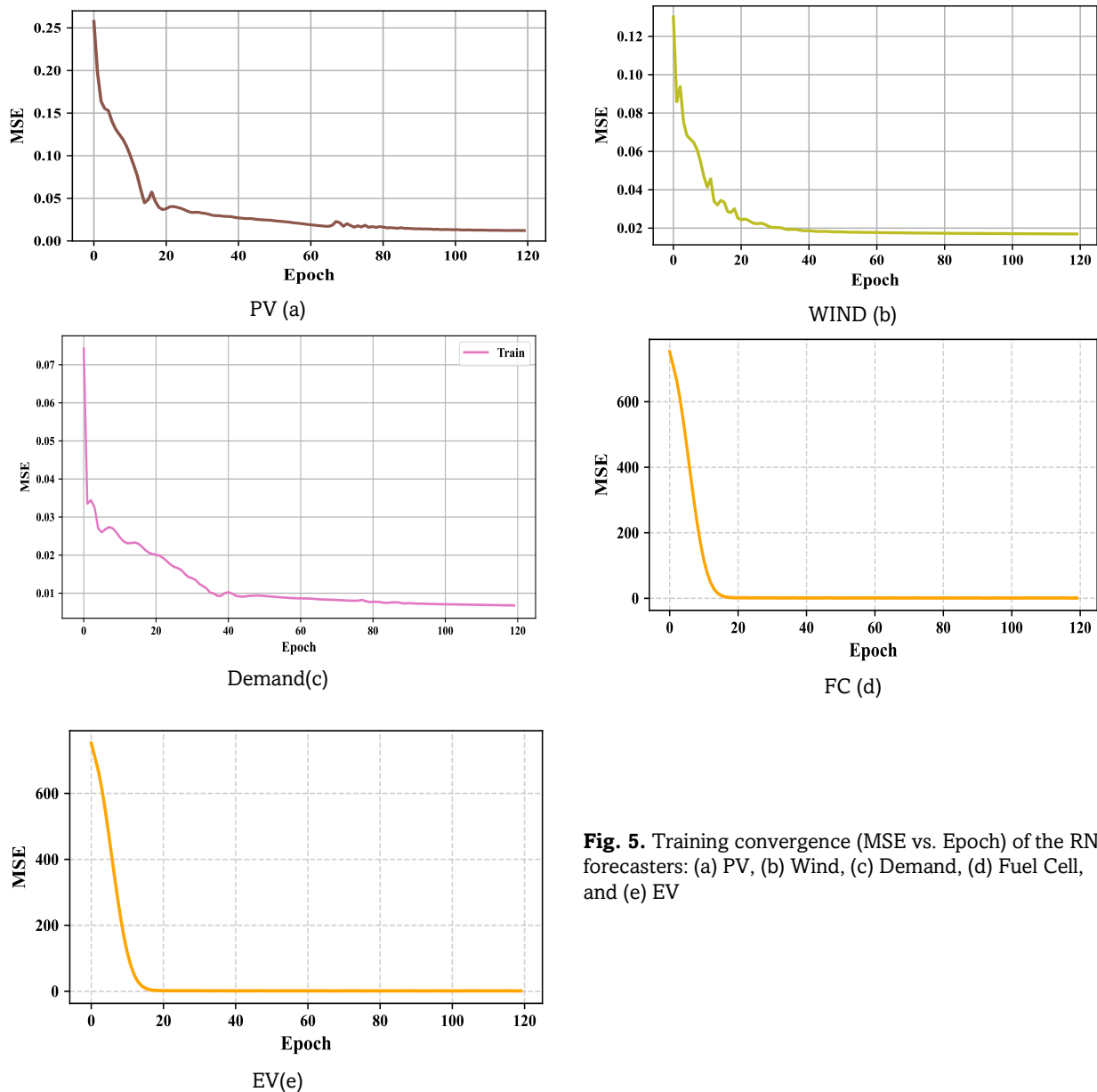


Fig. 5. Training convergence (MSE vs. Epoch) of the RNN forecasters: (a) PV, (b) Wind, (c) Demand, (d) Fuel Cell, and (e) EV

Table 2
Multi-horizon (1 h, 24 h, and 168 h) forecasting performance for the energy series.

Series	Horizon	Samples	MAE	RMSE	R ²
PV	1	216	0.4233	0.5122	0.9688
	24	193	0.5103	0.6487	0.7575
	168	49	0.7042	0.8424	0.4817
Wind	1	216	0.3744	0.4608	0.9410
	24	193	0.4766	0.5325	0.6399
	168	49	0.6847	0.7113	0.4781
Demand	1	216	0.3583	0.4625	0.9162
	24	193	0.4710	0.6447	0.5449
	168	49	0.6220	0.8447	0.3679
Fuel Cell	1	216	0.3681	0.4810	0.9708
	24	193	0.4563	0.6149	0.7524
	168	49	0.5797	0.7310	0.4733
EV	1	216	0.3494	0.4705	0.9547
	24	193	0.4755	0.5539	0.7211
	168	49	0.7164	0.7923	0.3707

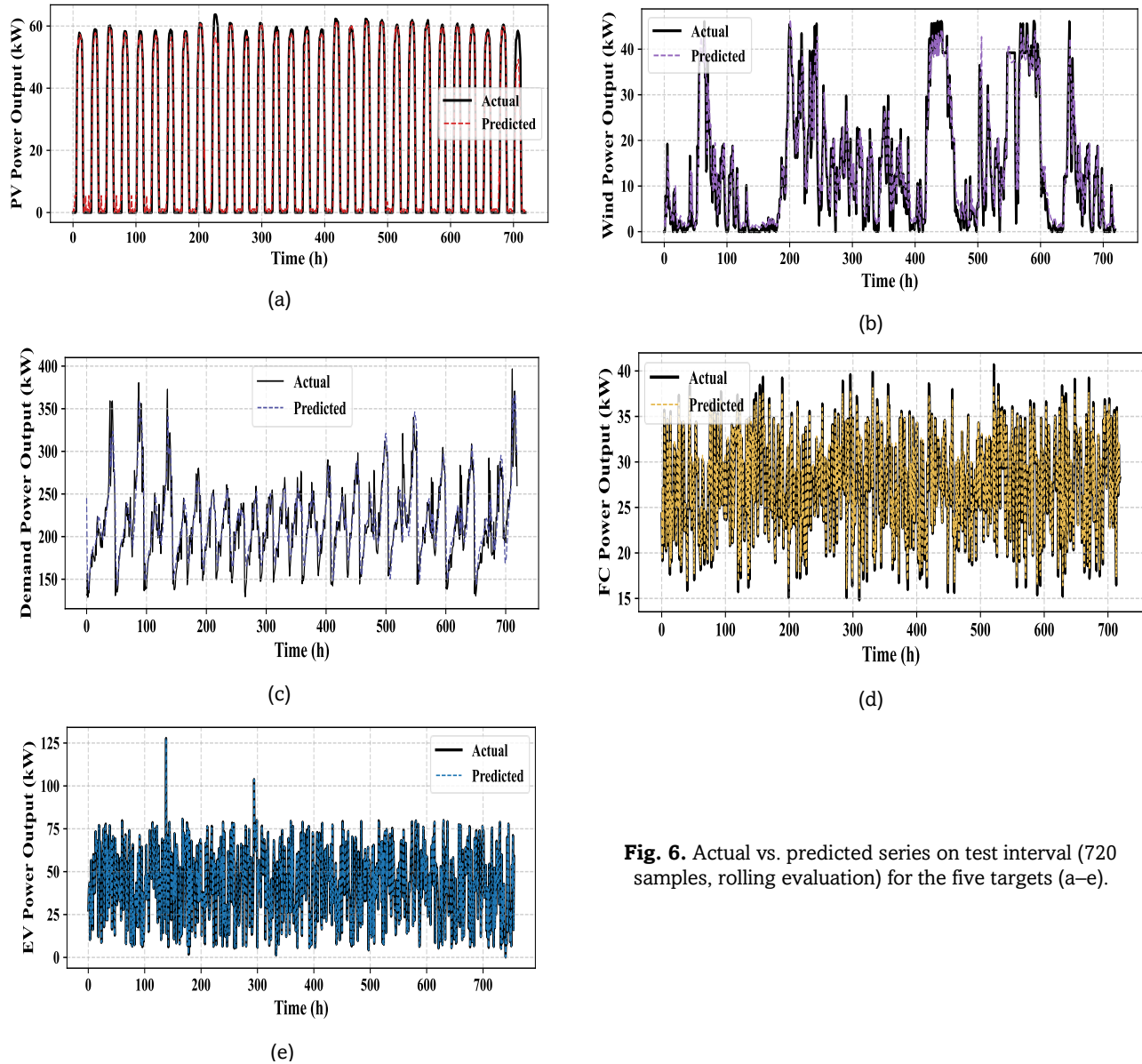


Fig. 6. Actual vs. predicted series on test interval (720 samples, rolling evaluation) for the five targets (a–e).

except the fuel-cell one exhibit smooth learning; however, the relatively high starting point of the error in the latter case is explained by the nature and scale of the data. The fuel-cell

model also shows a fast decline in MSE values. Small fluctuations in certain parts of the plots occur because such oscillations in neural networks are common and do not imply

an unstable training process. Overall, the convergence behavior indicates that the trained models can be used further to provide forecasted input values required for the energy management optimization process.

Table 2 demonstrates the forecasting accuracy of the RNN models for PV, wind, demand, fuel cell, and EV power at 1-hour, 24-hour, and 168-hour horizons. The maximum accuracy is observed for 1-hour-ahead forecasting because the R^2 values fall between 0.9162 and 0.9708, with minimum MAE/RMSE values. This indicates that the model has the ability to identify short-term temporal dependencies. When the forecast horizon increases from 1 hour to 24 hours and 168 hours, the error values become higher, and the R-squared values decrease, which is expected because forecasting uncertainty increases over longer horizons. However, despite this reduction, the 24-hour forecasts maintain the major characteristics of the energy profiles and can be used as input data in the EMS.

3.2.1. Prediction Quality

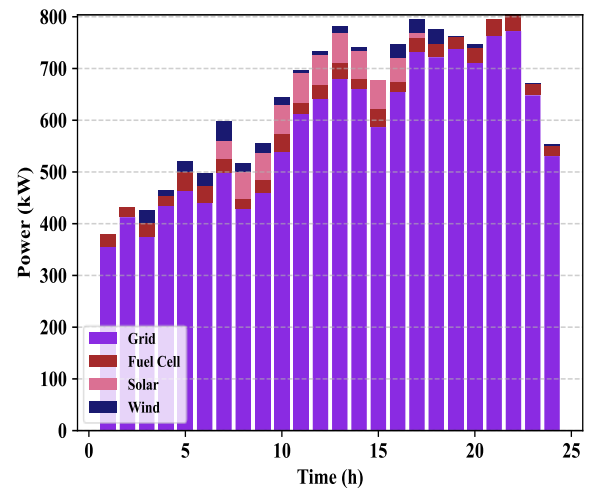
Fig. 6 depicts the comparison between real and forecasted profiles of PV, wind power, demand, fuel cell, and electric vehicle power over the testing period. From Fig. 6(a), it is observed that the PV prediction matches the typical pattern of daily generation very accurately, successfully detecting the production peaks during daytime and the absence of generation at night. From Fig. 6(b), it is evident that the wind power profile is more erratic compared to PV; however, the predicted curve successfully traces the major fluctuations and periods of intermittent generation. The demand profile prediction in Fig. 6(c) successfully reflects the typical load pattern as well as major demand peaks. It is significant to note that demand has an immediate effect on the grid-purchase decisions made by the EMS. It is seen from Fig. 6(d) and Fig. 6(e) that the predictions of fuel cell and EV power have high consistency, with discrepancies only during rapid fluctuations in the real profiles. This is expected because faster fluctuations are more difficult to predict using time-series forecasting methods. Overall, the agreement between real and forecasted profiles supports the use of the RNN outputs as inputs for the EMS optimization model.

3.3. EMS Results

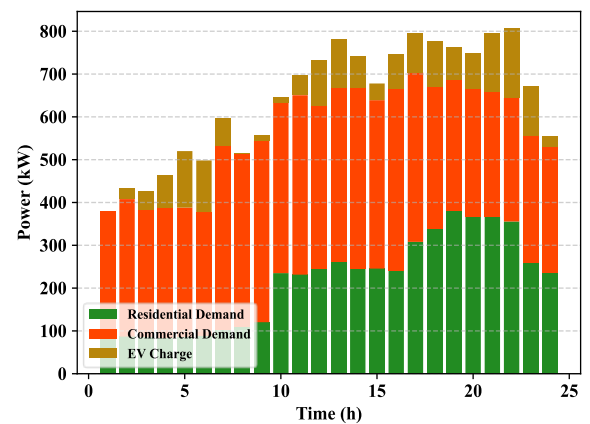
The operational behavior of the proposed framework is analyzed under two studied scenarios.

Scenario 1

Scenario 1 does not include a stationary BESS. Therefore, it can be seen from Fig. 7(a) that the share of grid contribution to the power supply constitutes the highest percentage throughout most hours of the day. At the same time, solar energy, wind power, and fuel cell power generation contribute to the power supply to a lesser extent. From this result, it can be concluded that the system has limited ability to shift renewable energy from time periods when it is available to time periods with high power demand. Hence, dependence on the grid is considerable, especially when renewable energy production is not sufficient to meet the growing power demand. It can be seen from Fig. 7(b) that the demand side includes both residential and commercial loads, while the EV charging load constitutes a flexible demand. Since no BESS is included in this scenario, EV charging scheduling alone cannot fully address the challenge of balancing supply and demand during peak hours.



(a)



(b)

Fig. 7. Scenario S1 with no storage.

Scenario 2

In Scenario 2, a fixed BESS is included in EVCS, which allows coordination between EV flexibility and BESS charging/discharging. As shown in Fig. 8(a), the supply side in the evening period does not rely on the grid as much as in Scenario 1.

The discharge of both BESS and EV becomes part of the demand-supply balance during the peak period with high electricity prices, especially from 19:00 to 24:00. It can be inferred that the presence of a storage system helps balance peak-time supply and thus reduces the need for purchasing electricity directly from the grid during high-price periods. Fig. 8(b) shows that EV and BESS charging mostly take place in earlier periods, when renewable power supply is higher and electricity prices are lower compared with the evening peak. Unlike Scenario 1, BESS in Scenario 2 provides another time-shifting mechanism, where energy storage occurs when electricity is cheaper, and the stored energy is discharged when demand peaks.

Scenario 2 performs clearly better than Scenario 1. In S2, charging is shifted to daylight hours: BESS charges alongside EVs during the PV plateau, and evening charging is largely avoided. On the supply side, S2 introduces coordinated BESS and EV discharging between 19:00 and 23:00, precisely when prices peak. These discharge blocks effectively replace the large grid imports observed during the same hours in S1, leading to

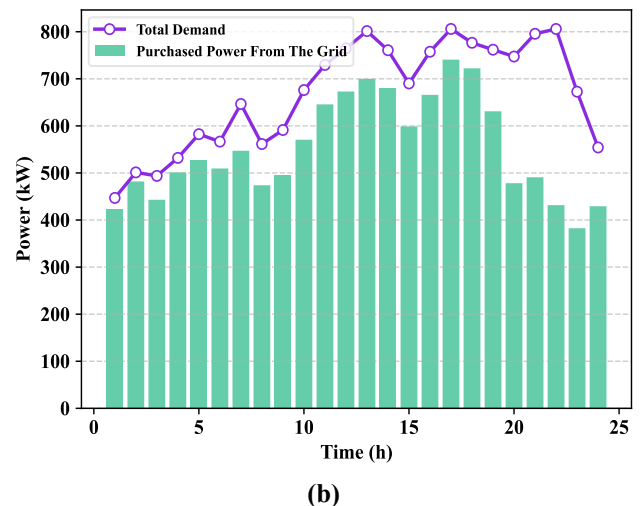
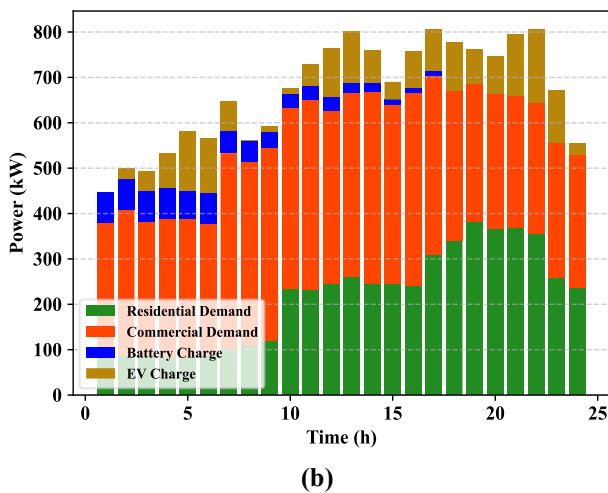
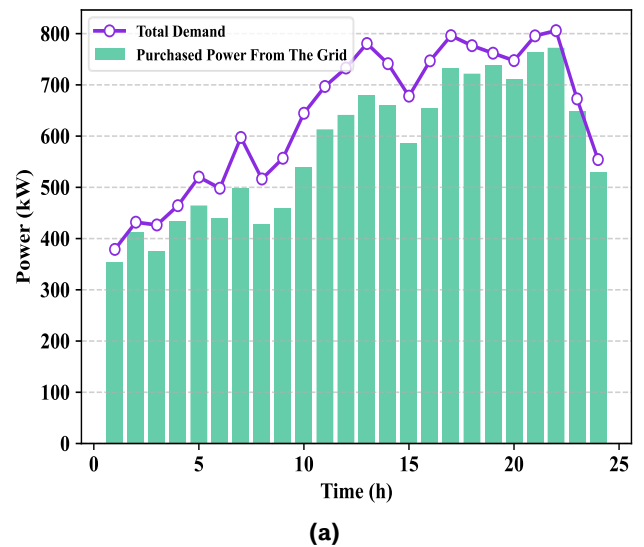
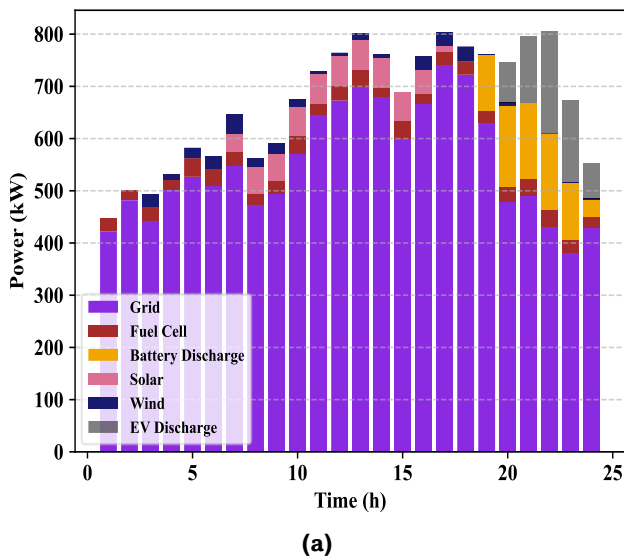


Fig. 8. Scenario S2 (with storage).

Fig. 9. Grid purchases vs. total demand across scenarios.

lower peak grid imports in S2. Midday grid purchases are also reduced because the BESS absorbs solar surplus and releases it later.

This can be explained by the limited flexibility of S1, where the transfer of energy is mainly controlled by the availability of EVs without a stationary BESS. This makes it difficult to reduce grid purchases during peak hours. However, incorporating a BESS in S2 changes the energy dispatch schedule by storing energy during favorable times marked by high production of renewable energy and low electricity costs. This energy is then dispatched during the evening peak times, thus reducing dependency on grid supply while meeting the state-of-charge requirements.

3.4. Scenario description of grid and FC usage

Fig. 9(a) shows total demand and purchased power from the grid over 24 hours. Without a BESS, grid purchases closely follow the demand, rising throughout the day and peaking in the evening, with only modest relief from local PV/wind and the fuel cell. No export is observed, and peak-hour supply relies predominantly on the grid. Fig. 9(b) displays the total demand and purchased power from the grid, as in Scenario 1 (S1), but now with a BESS. Compared to S1, the evening bars (19:00–24:00) are visibly lower by roughly 200 kW, indicating peak

shaving from coordinated EV/BESS discharge. In contrast, the early morning to midday bars are slightly higher and flatter, reflecting BESS charging when prices are moderate, and RESs are available. The net effect is a flatter purchase profile and reduced reliance on the grid during peak hours, especially in the evening, with no export observed.

The FC power profile adopted in the scheduling process is shown in Fig. 10 and covers a range of values between around 18 and 35 kW within 24 hours. The FC output changes within a limited operating range because the operational and ramping limits of the FC do not allow this device to follow all fast changes caused by EV load. Thus, the FC becomes an intermediate-level device for the optimization problem and is selected as a dispatchable source that helps cover slow changes of the remaining load after PV and wind contributions. In turn, BESS and V2G systems can accommodate faster changes while operating according to their own power and SoC constraints. Therefore, the FC provides a controlled contribution to the supply side and helps reduce grid dependence over the scheduling horizon.

3.5. Charge and discharge patterns of battery and EVs

Fig. 11 shows the synchronized charging and discharging schedule of BESS and EVs. BESS charges more from morning to

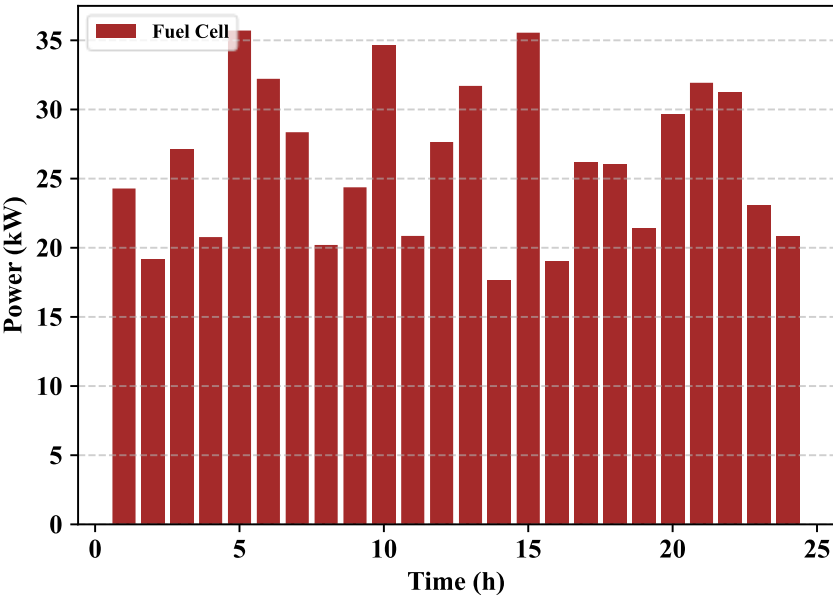


Fig. 10. Fuel cell output.

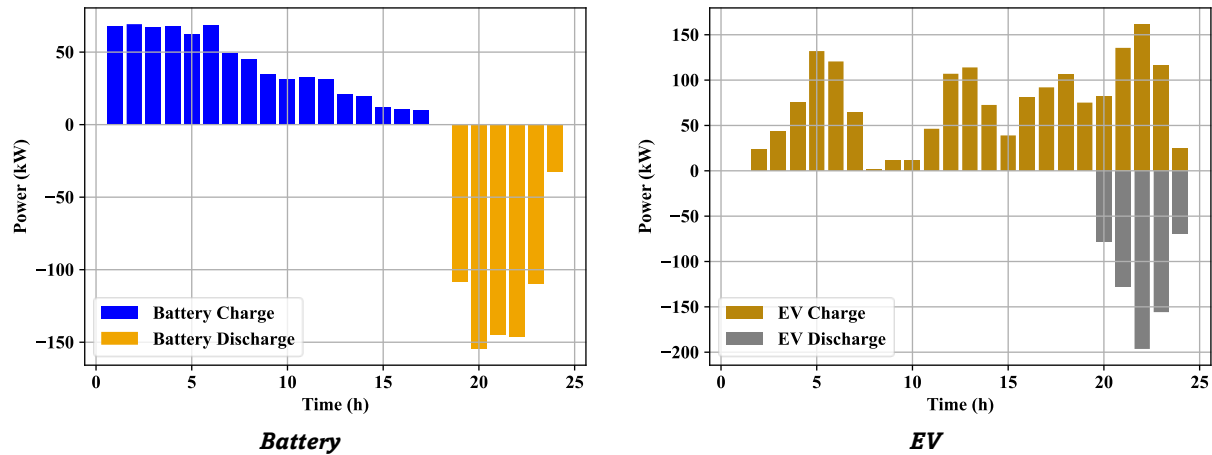


Fig. 11. Charge and discharge patterns under the proposed schedule.

Table 3			
Sensitivity analysis of operating cost and emission.			
Scenario	Sensitivity case	Cost (\$)	Emission (kg)
S1	Base	171833.86	13485.47
	Electricity price ×2	336308.27	13485.94
	RES availability ×0.7	174646.83	13720.20
S2	Base	160388.44	12892.22
	Electricity price ×2	314541.60	12891.69
	RES availability ×0.7	163064.28	13127.08

midday and discharges during peak hours in the evening, between around 19:00 and 24:00. Thus, it supports load shifting by utilizing periods with high renewable energy production and lower electricity rates. EVs charge based on availability, whereas V2G discharging occurs during the evening peak hours. Values with a positive sign represent charging, whereas those with a negative sign represent discharging. From this observation, it is clear that the use of storage and EV flexibility has been considered without violating operational constraints.

3.6. Best solution and multi-objective outcome

The results from both scenarios are evaluated according to two criteria: operating cost f_1 and emissions f_2 , where the Pareto fronts from the obtained solutions are shown in Fig. 12(a) for Scenario S1 and Fig. 12(b) for Scenario S2. In S1, the best solution point resulted in an operating cost of \$171,833.86 and emissions of 13,485.48 kg. In Scenario S2, a better solution is found, where the two objectives are reduced

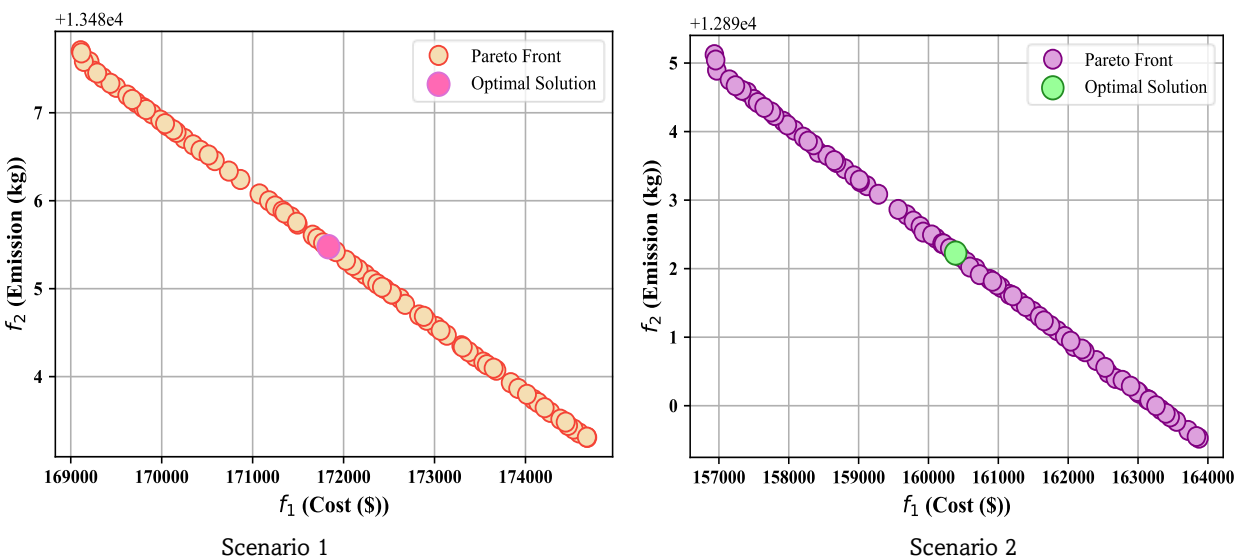


Fig. 12. Multi-objective trade-offs for the two scenarios.

Table 4
Comparison of the proposed study with representative related work.

Study	Forecasting model	System scope	BESS	V2G	Optimization target	Key reported outcome
(Ozkan <i>et al.</i> , 2022)	Not forecasting-centered	EV charging/discharging station with PV-battery-grid	Yes	Yes	Operational efficiency / cost	Reduced consumption, peak demand, and cost
(Baherifard <i>et al.</i> , 2022)	Not forecasting-centered	Commercial parking lot charging stations	No explicit integrated BESS scheduling focus	No	Planning and network imbalance	23% increase in EV user profit, 30% reduction in imbalance
(Aldossary <i>et al.</i> , 2024)	LSTM-based SARLDNet	EVCS energy forecasting	No operational scheduling focus	No	Forecast accuracy	MAPE = 7.2%, RMSE = 22.3 kWh, ($R^2 = 0.87$)
(Chengyu Yang <i>et al.</i> , 2024)	Attention-SLSTM	EV charging-demand forecasting	No operational scheduling focus	No	Forecast accuracy	MAE = 1.6860, RMSE = 2.5040, MAPE = 9.768%
(Koca, 2025)	DNN-based control / load shedding	Hybrid PV-wind EV battery charging station connected to the grid	No explicit stationary BESS focus	No	cost reduction, and grid-load reduction	Improved load shedding and, system stability
This study	RNN	EVCS with PV, wind, FC, BESS, and V2G	Yes	Yes	Bi-objective cost and emission optimization	($R^2 = 0.9708$); cost ↓ 6.7%; emissions ↓ 4.4%

to \$160,388.44 and 12,892.23 kg for operating cost and emissions, respectively. Compared to Scenario S1, Scenario S2 saves \$11,445, that is, 6.7% in cost, and reduces emissions by 593 kg, that is, 4.4%. The Pareto set for Scenario S2 moves toward a low-cost and low-emissions domain compared to Scenario S1. As such, the benefits mainly result from storage implementation, where renewable generation can be stored for evening discharge, leading to lower grid usage during peak hours and lower related emissions.

As illustrated in Table 3, sensitivity analysis is performed for two cases: doubling the electricity purchase price and reducing renewable resource availability by 30%. In all considered cases, Scenario 2 shows better results in terms of cost and emissions compared with Scenario 1, which indicates the operational benefit of using the BESS. In both scenarios, the increased electricity price results in higher operating costs, while emissions remain almost unchanged because the emission factors are independent of electricity prices. The reduction in renewable energy availability leads to increased costs and

emissions. However, Scenario 2 still performs better than Scenario 1, confirming that BESS improves scheduling flexibility under stressed operating conditions.

Table 4 provides a comparison between the suggested approach and previous works on EVCS and microgrids. This work differs significantly from previous studies, which mainly concentrate on forecasting, planning, or individual operational aspects. The current research includes RNN-based forecasting, BESS technology, V2G function, fuel cell support, and cost-emission optimization through NSGA-II within a comprehensive EVCS scheduling system.

4. Conclusion

The current study presents a new deep learning-based approach for optimizing EVCS operations by managing interrelations between energy supply, EV demand, and energy storage in conjunction with using renewable energy sources,

energy storage systems, and V2G capabilities, while also taking into account variations in prices and network conditions. Specifically, RNNs have been implemented to provide short-term forecasts and optimize operations. A hybrid system with solar and wind generators combined with fuel cells and battery storage systems demonstrates flexibility to changes in renewable availability. The battery storage systems store energy during periods of low loads and discharge it when needed. Furthermore, the use of V2G technology enables electric vehicles to discharge energy to the grid during periods of high electricity demand, thereby supporting peak-period load balancing. This integration decreases reliance on grid resources, operating costs, and emissions, especially in times of high prices and high demand, resulting in a 6.7% reduction in costs and a 4.4% reduction in emissions in Scenario 2 compared with Scenario 1.

In addition, the use of ESS together with V2G technology allows for better load balancing by the energy grid during peak-load periods and thus increases overall efficiency. Overall, this study provides an advanced, cost-efficient, and environmentally friendly technology for the development of EVCS, which can be considered as a contribution toward the development of future energy infrastructures to meet the increasing needs of electric car usage and reduce environmental footprint.

Possible areas for future research may include improvement in the use of artificial intelligence and machine learning technologies in the prediction of energy demand and its real-time distribution. In addition, the scalability of the proposed approach for extensive EVCS networks might be considered. Future studies may extend the forecasting layer by analyzing the performance of gated recurrent models and state-of-the-art transformer architectures for time-series forecasting based on a unified framework.

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