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Multi-Stage Dynamic Programming Design and Life-Cycle Economic Analysis of a Photovoltaic-Storage-Charging System in the Hasuhai Expressway Service Area

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Abstract

To improve the long-term adaptability of photovoltaic-storage-charging systems under rapidly increasing electric vehicle charging demand, this study develops a multi-stage dynamic programming and life-cycle economic assessment framework for the Hasuhai expressway service area in Inner Mongolia, China. A SARIMA-Holt-Winters hybrid forecasting model was used to predict future load growth, and a phased capacity expansion scheme was established for photovoltaic generation, energy storage, and charging facilities. The results show that the annual average load is projected to increase by approximately 11.22 times from 2026 to 2045, indicating that the one-time construction scheme may face long-term supply insufficiency despite its favorable short-term economic performance. Compared with the initial scheme, the multi-stage planning scheme improves long-term adaptability by dynamically expanding photovoltaic capacity, energy storage capacity, and charging ports according to load growth. The optimized scheme increases the net present value from 33.094 million CNY to 57.347 million CNY, reduces the levelized cost of charging to 0.171 CNY/kWh, and increases the 25-year carbon emission reduction to 62,490 tCO₂. Sensitivity analysis indicates that the charging service fee has the greatest influence on project economics, followed by the grid electricity price and discount rate. The proposed framework provides a practical reference for the phased construction and investment decision-making of photovoltaic-storage-charging systems in expressway service areas with rapidly growing charging demand.

Keywords: expressway service area; photovoltaic-storage-charging system; multi-stage dynamic programming; carbon emission reduction; dynamic capacity expansion; life-cycle economic performance



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1. Introduction

Against the background of global climate change and energy transition, the decarbonization of energy systems has become an important direction for the development of transportation infrastructure. Since China proposed the strategic goals of achieving carbon peaking before 2030 and carbon neutrality before 2060, distributed photovoltaic generation, energy storage systems, and electric vehicle charging infrastructure have been increasingly investigated as key technologies for reducing fossil-energy dependence and improving

transport-sector energy flexibility [1,2]. Expressway service areas integrate public services, commercial operation, and vehicle energy replenishment, and therefore exhibit distinct scenario-specific energy consumption characteristics. Existing studies on expressway service areas have shown that the rapid growth of electric vehicles can substantially reshape service-area load curves and increase peak charging demand [3,4]. By the end of 2025, the number of new energy vehicles in China had reached 43.97 million, among which 30.22 million were battery electric vehicles, accounting for 68.74% of the total new energy vehicle fleet [5]. By the end of April 2026, the total number of electric vehicle charging facilities nationwide had reached 21.955 million, representing a year-on-year increase of 47.4% [6]. The large-scale development of new energy vehicles and the rapid expansion of charging infrastructure have imposed higher requirements on charging service capacity, power supply reliability, and operational economy in expressway service areas.

Photovoltaic-storage-charging systems provide a feasible pathway for the energy transition of expressway service areas. Distributed photovoltaic generation is characterized by a short construction period, strong on-site consumption capability, and close spatial coupling with local loads, thereby reducing the dependence of service areas on electricity purchased from the conventional power grid [7,8]. Previous studies on photovoltaic electric vehicle charging stations with battery storage have shown that local photovoltaic generation and storage can reduce grid dependence, energy costs, and carbon emissions under suitable charging scenarios [9,10]. Energy storage systems can smooth photovoltaic output fluctuations and enhance system operational flexibility through peak shaving, valley filling, peak–valley arbitrage, and emergency backup functions [11,12]. For expressway service areas, parking areas, building rooftops, vacant station land, and surrounding spaces can be utilized for photovoltaic deployment, while energy storage can mitigate the impact of peak charging loads on the power grid [3,13]. Inner Mongolia is endowed with abundant solar energy resources, long sunshine duration, and high atmospheric transparency, providing favorable natural conditions for the development of distributed photovoltaics and integrated photovoltaic-storage-charging systems [14]. Therefore, planning research on photovoltaic-storage-charging systems in expressway service areas in Inner Mongolia is expected not only to improve the utilization level of clean energy, but also to provide engineering references for the low-carbon development of transportation infrastructure.

Existing studies related to photovoltaic-storage-charging systems can be divided into several research streams. The first stream focuses on electricity load forecasting. Statistical forecasting frameworks have been developed for long-term district energy load prediction, and hybrid models combining machine learning with ARIMA-type methods have been used to improve the representation of nonlinear and periodic load variations [15,16]. SARIMA-based models have also been shown to be effective in capturing seasonal fluctuations in power load series [17]. In addition, Holt-Winters models have been used to describe time series with trend and seasonal components, providing a useful basis for medium- and long-term load forecasting [18,19]. These studies provide methodological support for load forecasting, but most of them focus on general power systems, urban energy systems, or distribution transformer areas rather than the charging-load evolution of expressway service areas.

The second stream concerns the sizing and operation of photovoltaic, energy storage, and electric vehicle charging systems. Previous studies have optimized the configuration of electric vehicle charging stations by jointly considering charging ports, photovoltaic capacity, and energy storage ratings [20]. Mixed-integer linear programming models have also been developed for sizing photovoltaic and battery energy storage systems in extreme fast charging stations while accounting for uncertainty and battery degradation [9]. Technical, financial, and environmental feasibility assessments further indicate that pho-

photovoltaic charging stations with local battery storage can reduce grid dependence and carbon emissions under appropriate charging scenarios [10]. These studies demonstrate the technical feasibility of integrating photovoltaic generation and energy storage into charging infrastructure, but they generally emphasize static sizing or operational optimization rather than staged expansion under long-term load growth.

The third stream focuses on multi-stage planning and coordinated energy system optimization. Multi-stage photovoltaic siting and sizing studies have shown that classified load growth should be considered when determining distributed photovoltaic capacity [21]. Coordinated photovoltaic-storage planning methods further indicate that dynamic load characteristics can significantly influence optimal storage capacity and system economics [22]. Dynamic multi-stage planning methods for integrated energy systems have also been proposed to better match equipment investment with the evolution of energy demand over the planning horizon [23]. These findings support the use of dynamic planning for systems with gradually increasing loads; however, their application to expressway service areas with rapidly increasing electric vehicle charging demand remains limited.

The fourth stream is related to renewable energy applications and life-cycle assessment in transportation infrastructure. Studies on zero-carbon expressway service areas, expressway charging-load modeling, and photovoltaic-storage-battery-swapping energy management have provided useful references for the low-carbon transformation of service areas [3,4,13]. Life-cycle environmental assessment of electric vehicle charging infrastructure has shown that charger manufacturing, operation, electricity mix, and end-of-life treatment can influence the overall environmental burden of charging systems [24]. Economic and policy studies have also incorporated energy storage operation modes, electric vehicle charging pricing, and carbon trading benefits into project evaluation frameworks [25–27]. Nevertheless, relatively few studies have established a complete analytical chain that links long-term load forecasting, staged capacity expansion, life-cycle economic assessment, carbon emission reduction, and sensitivity analysis for expressway service areas.

Although existing studies have provided an important foundation for the planning of photovoltaic-storage-charging systems, several limitations remain. First, some studies have focused on static load conditions or a single planning horizon, while the dynamic characteristics of charging loads in expressway service areas, which continuously evolve with the growth of new energy vehicles, have not been sufficiently considered. Second, load forecasting, capacity configuration, and economic assessment have often been conducted independently, and a complete analytical chain from load evolution to capacity expansion and life-cycle economic evaluation is still lacking. Third, one-time construction schemes are commonly adopted in engineering practice. Although such schemes are relatively simple to implement in the initial stage and may achieve rapid investment recovery, staged mismatches may occur under rapid load growth scenarios, including early-stage capacity redundancy, long-term supply shortages, and weakened energy storage regulation capability. Therefore, a multi-stage dynamic planning method for the coordinated expansion of photovoltaic, energy storage, and charging facilities should be established based on the load growth process of service areas, and its long-term economic performance and environmental benefits should be comprehensively evaluated.

Therefore, this study aims to develop a load-forecasting-driven multi-stage dynamic planning framework for a photovoltaic-storage-charging system in an expressway service area. The main contributions are as follows: (1) a SARIMA-Holt-Winters hybrid forecasting method is coupled with staged capacity expansion planning to describe the load evolution of an expressway service area; (2) a multi-stage planning model is established by integrating photovoltaic capacity, energy storage capacity, charging facility expansion, and life-cycle economic assessment; and (3) the long-term economic performance, carbon emission

reduction benefits, financial risk resistance, and adaptability of the phased expansion scheme are compared with those of a one-time construction scheme under uncertainties in electricity price, charging service fee, and discount rate.

The remainder of this paper is organized as follows. Section 2 describes the study area, data sources, forecasting model, evaluation indicators, multi-stage planning model, and economic assessment method. Section 3 presents the forecasting results, baseline scheme evaluation, staged capacity expansion results, and economic performance. Section 4 discusses the methodological contribution, applicability of long-term forecasting, practical limitations, safety considerations, and future extensions. Section 5 summarizes the main conclusions.

2. Materials and Methods

2.1. Study Area and Initial System Configuration

The Hasuhai expressway service area in Hohhot, Inner Mongolia Autonomous Region, was selected as the research object. The service area is located along the G6 Expressway and is equipped with relatively well-developed transportation, communication, and supporting infrastructure. It represents a typical integrated energy application scenario for expressway service areas. The region where the service area is located has favorable solar irradiation conditions and a relatively dry climate, providing suitable natural conditions for distributed photovoltaic deployment. According to data from Solargis (Solargis s.r.o., Bratislava, Slovakia), the multi-year average total solar radiation in the project area is 1664.4 kWh/m². Based on the Assessment Method for Solar Energy Resource Grades, the area can be classified as a region with “very abundant” solar energy resources.

A new-energy photovoltaic-storage ultra-fast charging station has been constructed in the Hasuhai service area, and a certain foundation of photovoltaic generation, energy storage, and charging facilities has been established. To clarify the resource conditions and initial system configuration of the research object, the basic conditions and initial system configuration of the Hasuhai service area are presented in Table 1.

Table 1. Basic conditions and initial system configuration of the Hasuhai service area.

Category	Main Information
Location	Hasuhai expressway service area, Hohhot, Inner Mongolia, along the G6 Expressway
Solar resource	Multi-year average total solar radiation: 1664.4 kWh/m ² ; resource grade: very abundant
Initial PV system	1.74 MW; 2784 N-type monocrystalline double-glass modules
Initial energy storage system	1200 kW/2400 kWh; two 600 kW/1200 kWh units
Existing charging facilities	14 chargers and 24 charging connectors
Total charging power	4900 kW; 4 liquid-cooled ultra-fast charging connectors and 10 dual-connector DC fast chargers

As shown in Table 1, the Hasuhai service area has favorable solar energy resources and has been equipped with a 1.74 MW photovoltaic system, a 1200 kW/2400 kWh energy storage system, and 4900 kW of charging facilities. Therefore, it can be regarded as a representative case for the dynamic planning of photovoltaic-storage-charging systems in expressway service areas. In the subsequent analysis, this initial system is used as the baseline scheme. Its long-term adaptability is evaluated by combining the load forecasting results, and a multi-stage dynamic planning scheme is further developed.

2.2. Data Sources and Load Characteristics

Daily-scale electricity load data from 2016 to 2025 were collected for the Hasu hai service area and used as the basis for load characterization and forecasting. The dataset contains 3650 daily load samples and can reflect load variations at annual, monthly, and weekly scales. These data were used to identify the historical growth pattern and periodic characteristics of the service area load and to provide the input series for the SARIMA-Holt-Winters hybrid forecasting model.

2.3. Load Forecasting Method and Model Validation

The electricity load of expressway service areas is jointly affected by traffic flow, holiday travel demand, seasonal climatic conditions, and the charging demand of new energy vehicles. It generally exhibits both a long-term growth trend and periodic fluctuations. Since a single time-series model is usually unable to simultaneously capture long-term trend extrapolation and periodic fluctuation characteristics, a SARIMA-Holt-Winters hybrid model was adopted in this study to forecast the future load of the service area.

The SARIMA model is suitable for time-series data with seasonal and periodic characteristics. Periodic fluctuations in the load series can be extracted through differencing, autoregressive terms, and moving-average terms, and its general form is expressed in Equation (1).

$$SARIMA(p, d, q)(P, D, Q)s \quad (1)$$

where p , d and q denote the non-seasonal autoregressive order, differencing order, and moving-average order, respectively; P , D , and Q denote the seasonal autoregressive order, seasonal differencing order, and seasonal moving-average order, respectively; and s represents the seasonal period. In contrast, the Holt-Winters model updates the level, trend, and seasonal components recursively, and therefore can effectively characterize the long-term growth trend of the load series.

In this study, the Holt-Winters forecasting result was used as the long-term trend baseline, and the periodic correction factor extracted from the SARIMA model was employed to correct the weekly and annual periodic fluctuations in the load series. Specifically, the historical load series was first fitted and forecasted using the SARIMA model to obtain a predicted series containing periodic fluctuation characteristics. Then, the SARIMA-predicted value at time t was normalized by the mean value of the predicted series within the corresponding periodic window, and the periodic correction factor was obtained, as expressed in Equation (2).

$$C_t = \frac{\hat{y}_t^{SARIMA}}{\bar{y}_t^{SARIMA}} \quad (2)$$

where C_t denotes the periodic correction factor at time t ; $\hat{y}_t^{SARIMA}$ denotes the predicted value obtained from the SARIMA model at time t ; and $\bar{y}_t^{SARIMA}$ denotes the mean value of the SARIMA-predicted series within the corresponding periodic window. For the forecasting horizon $T + h$, C_{T+h} can be obtained using the same procedure. A correction factor greater than 1 indicates that the load at the corresponding time is higher than the periodic average level, whereas a value lower than 1 indicates that the load is lower than the periodic average level. The final hybrid forecasting model is expressed in Equation (3).

$$\hat{Y}_{T+h} = \hat{y}_{T+h}^{HW} \cdot C_{T+h} \quad (3)$$

where $\hat{Y}_{T+h}$ denotes the predicted value of the hybrid model at time $T + h$; $\hat{y}_{T+h}^{HW}$ denotes the predicted value obtained from the Holt-Winters model; and C_{T+h} denotes the periodic correction factor derived by normalizing the SARIMA-predicted series. In this hybrid frame-

work, the long-term growth trend is retained by the Holt-Winters model, while seasonal and weekly fluctuations are corrected using the SARIMA-based periodic correction factor.

To strengthen the validation of the forecasting model, three widely used performance metrics are introduced: mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE). These metrics are used to quantify the absolute deviation, overall prediction error, and relative forecasting error. These indicators are calculated using Equations (4)–(6), respectively.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (5)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\% \quad (6)$$

where y_i and $\hat{y}_i$ denote the observed and predicted load values, respectively, and n denotes the number of validation samples. In this study, the forecasting performance was evaluated using the validation dataset. The calculated MAE, RMSE, and MAPE values were used to assess whether the hybrid forecasting model could provide reliable load inputs for subsequent capacity planning.

2.4. Evaluation Indicators for the Baseline Scheme

To evaluate the long-term adaptability of the one-time construction mode, the initial photovoltaic-storage-charging system proposed by the project owner was used as the baseline scheme and was assessed from the perspectives of technical matching and economic performance.

The technical matching assessment mainly includes the photovoltaic self-sufficiency rate, energy storage regulation capability, supply–demand balance coefficient of charging facilities, and charger utilization rate. The photovoltaic self-sufficiency rate is used to reflect the extent to which photovoltaic power generation can cover the electricity demand of the service area. The energy storage regulation capability is used to characterize the smoothing effect of energy storage capacity on daily load fluctuations. The supply–demand balance coefficient of charging facilities is used to indicate the capacity margin of charging facilities relative to the forecasted load. The charger utilization rate is used to determine whether charging facilities suffer from early-stage idleness or long-term supply insufficiency. These indicators are calculated using Equations (7)–(10), respectively.

$$\eta_{self} = \frac{E_{PV}}{E_{load}} \times 100\% \quad (7)$$

where η_{self} denotes the photovoltaic self-sufficiency rate; E_{PV} denotes the annual power generation of the photovoltaic system; and E_{load} denotes the annual electricity consumption of the service area.

$$\eta_{reg} = \frac{E_{ESS}}{E_{load,day}} \times 100\% \quad (8)$$

where η_{reg} denotes the energy storage regulation capability; E_{ESS} denotes the energy storage capacity; and $E_{load,day}$ denotes the average daily electricity consumption of the service area.

$$\eta_{balance} = \frac{P_{installed}}{P_{avg,forecast}} \quad (9)$$

$$\eta_{util} = \frac{P_{avg,forecast}}{P_{installed}} \times 100\% \quad (10)$$

where $P_{installed}$ denotes the total installed power of charging facilities; and $P_{avg,forecast}$ denotes the forecasted average charging power.

For the economic assessment, total investment, operating revenue, operation and maintenance cost, net present value, internal rate of return, payback period, levelized cost of charging, and carbon emission reduction benefits were selected as the evaluation indicators. Through the combined assessment of technical matching and economic performance, the adaptability of the initial one-time construction scheme under different load growth stages can be identified.

2.5. Multi-Stage Dynamic Planning Model

To address the insufficient long-term adaptability of the one-time construction scheme under continuous load growth, a multi-stage dynamic planning model was established in this study. The planning horizon was set from 2026 to 2050 and was divided into five stages, with each five-year period defined as one decision-making stage. Among them, 2026–2045 was regarded as the main period for load growth and capacity expansion, while 2046–2050 was defined as the stable operation period. A “phased construction and dynamic expansion” strategy was adopted, through which the additional capacities of photovoltaic generation, energy storage, and charging facilities were determined stage by stage.

Let k denote the planning stage, where $k = 1, 2, \dots, K$, and $K = 5$. The main decision variables include the cumulative photovoltaic installed capacity P_k^{PV} , energy storage capacity E_k^{ESS} , energy storage power P_k^{ESS} , and the numbers of slow, fast, and ultra-fast charging ports, denoted as N_k^s , N_k^f , and N_k^u , respectively. The corresponding incremental capacities in stage k are denoted as ΔP_k^{PV} , ΔE_k^{ESS} , ΔP_k^{ESS} , ΔN_k^s , ΔN_k^f , and ΔN_k^u .

The objective of the model is to minimize the life-cycle net present cost, as expressed in Equation (11):

$$\min NPC = \sum_{k=1}^K \frac{C_k^{inv} + C_k^{om} + C_k^{rep} + C_k^{grid} - R_k^{ch} - R_k^{carb}}{(1+r)^{y_k}} \quad (11)$$

where NPC is the life-cycle net present cost; C_k^{inv} , C_k^{om} , C_k^{rep} , and C_k^{grid} denote the investment cost, operation and maintenance cost, replacement or aging cost, and grid electricity purchase cost in stage k , respectively; R_k^{ch} and R_k^{carb} denote the charging service revenue and carbon emission reduction revenue, respectively; r is the discount rate; and y_k is the representative year of stage k .

The charging facility capacity should satisfy the forecasted peak charging demand in each stage, as shown in Equation (12):

$$P_k^{pile} = p_s N_k^s + p_f N_k^f + p_u N_k^u \geq P_k^{peak} \quad (12)$$

where P_k^{pile} is the total installed charging power in stage k ; p_s , p_f , and p_u are the rated powers of slow, fast, and ultra-fast charging ports, respectively; and P_k^{peak} is the forecasted peak charging load in stage k .

The photovoltaic output constraint is expressed in Equation (13):

$$0 \leq P_{k,t}^{PV} \leq P_k^{PV} \cdot \phi_t^{PV} \quad (13)$$

where $P_{k,t}^{PV}$ is the photovoltaic output at time t in stage k , and ϕ_t^{PV} is the normalized photovoltaic output coefficient determined by local solar radiation conditions.

The energy storage charging and discharging power constraints are expressed in Equations (14) and (15):

$$0 \leq P_{k,t}^{ch} \leq P_k^{ESS} \quad (14)$$

$$0 \leq P_{k,t}^{dis} \leq P_k^{ESS} \quad (15)$$

where $P_{k,t}^{ch}$ and $P_{k,t}^{dis}$ are the charging and discharging powers of the energy storage system at time t , respectively.

The state-of-charge constraint of the energy storage system is expressed in Equations (16) and (17):

$$SOC_{k,t+1} = SOC_{k,t} + \frac{\eta_{ch} P_{k,t}^{ch} \Delta t}{E_k^{ESS}} - \frac{P_{k,t}^{dis} \Delta t}{\eta_{dis} E_k^{ESS}} \quad (16)$$

$$SOC^{min} \leq SOC_{k,t} \leq SOC^{max} \quad (17)$$

where $SOC_{k,t}$ is the state of charge of the energy storage system at time t in stage k ; η_{ch} and η_{dis} are the charging and discharging efficiencies, respectively; Δt is the time interval; and SOC^{min} and SOC^{max} are the lower and upper limits of the allowable state-of-charge range.

The system power balance constraint is expressed in Equation (18):

$$P_{k,t}^{PV} + P_{k,t}^{dis} + P_{k,t}^{grid} = P_{k,t}^{load} + P_{k,t}^{ch} + P_{k,t}^{cur} \quad (18)$$

where $P_{k,t}^{grid}$ is the power purchased from the grid; $P_{k,t}^{load}$ is the service area load; and $P_{k,t}^{cur}$ is the curtailed photovoltaic power.

To reflect the phased construction principle, the cumulative capacities of photovoltaic generation, energy storage, and charging facilities should satisfy the staged expansion monotonicity constraints:

$$P_k^{PV} \geq P_{k-1}^{PV}, E_k^{ESS} \geq E_{k-1}^{ESS}, P_k^{ESS} \geq P_{k-1}^{ESS} \quad (19)$$

$$N_k^s \geq N_{k-1}^s, N_k^f \geq N_{k-1}^f, N_k^u \geq N_{k-1}^u \quad (20)$$

The corresponding incremental capacities should be non-negative:

$$\Delta P_k^{PV}, \Delta E_k^{ESS}, \Delta P_k^{ESS}, \Delta N_k^s, \Delta N_k^f, \Delta N_k^u \geq 0 \quad (21)$$

The model was solved by combining the load forecasting results, staged capacity constraints, and life-cycle economic assessment module. The forecasting and planning calculations were implemented using Python 3.10.13 (Python Software Foundation, Wilmington, DE, USA). The SARIMA and Holt-Winters models were implemented using the statsmodels package, while numerical calculation, scenario comparison, and sensitivity analysis were conducted using NumPy and pandas. The economic calculation results were further checked using Microsoft Excel 2021 (Microsoft Corporation, Redmond, WA, USA). Python was selected because it provides transparent and reproducible open-source libraries for time-series forecasting, numerical computation, and scenario analysis, while Excel was used for cross-checking the financial indicators and tabulated results.

2.6. Life-Cycle Economic Assessment and Sensitivity Analysis

To compare the comprehensive performance of different construction modes, a life-cycle cost-benefit analysis method was adopted to evaluate the one-time construction scheme and the multi-stage planning scheme. The economic evaluation indicators include net present value, internal rate of return, payback period, levelized cost of charging, and

carbon emission reduction benefits. Among them, the levelized cost of charging is used to represent the life-cycle cost corresponding to unit charging electricity; a lower value indicates better long-term economic performance. Furthermore, the grid electricity price, charging service fee, and discount rate were selected as sensitivity factors to analyze the effects of external parameter variations on project economics.

The economic assessment was conducted based on explicitly defined assumptions for investment cost, operation and maintenance cost, electricity purchase price, charging service fee, discount rate, carbon price, carbon emission factor, and revenue calculation. These parameters form the basis for the life-cycle cost–benefit analysis and sensitivity assessment.

Specifically, the baseline grid electricity purchase price was set as 0.550 CNY/kWh, and a variation range of 0.495–0.605 CNY/kWh was used in the sensitivity analysis to represent a $\pm 10\%$ fluctuation in electricity purchase cost. The charging service fee was set as 0.50 CNY/kWh, with a sensitivity range of 0.45–0.55 CNY/kWh. The discount rate was set as 9.5%, and a wider range of 7.6–11.4% was adopted to reflect the influence of financing cost and capital recovery uncertainty. Carbon revenue was calculated by multiplying the estimated carbon emission reduction by the carbon revenue coefficient. According to the calculated present value of carbon revenue and the cumulative carbon emission reduction, the effective carbon revenue coefficient used in this study was approximately 25 CNY/tCO₂.

The charging revenue was calculated based on the cumulative charging electricity and the charging service fee, while the grid electricity purchase cost was calculated based on the amount of electricity purchased from the grid and the grid electricity purchase price. The carbon emission reduction benefit was included as an additional environmental revenue item. Therefore, the net cash flow of each stage was determined by subtracting investment cost, operation and maintenance cost, replacement cost, and grid electricity purchase cost from charging service revenue and carbon revenue. These assumptions were used consistently in the comparison between the initial scheme and the multi-stage dynamic programming scheme.

3. Results

3.1. Historical Load Characteristics and Forecasting Results

As shown in Figure 1, the load of the service area exhibited an overall increasing trend from 2016 to 2025. The average daily electricity consumption increased from 157.95 kWh in 2016 to 501.52 kWh in 2025, indicating that the electricity demand of the service area gradually shifted from a low-load stage to a relatively high-load stage. The load growth can be mainly attributed to the increasing charging demand of new energy vehicles, the expansion of service area functions, and changes in traffic flow.

In addition to the long-term growth trend, the load of the service area also shows certain seasonal fluctuations and weekly periodic characteristics. The monthly load is affected by tourism travel, holiday traffic flow, temperature variation, and charging demand, and is relatively high in summer and during certain peak travel months. The weekly load is influenced by commuting traffic, logistics transportation, and expressway travel patterns, showing differences between weekdays and weekends. Therefore, the load series of the Hasuhai service area can be regarded as a non-stationary time series characterized by the superposition of long-term growth, seasonal fluctuations, and weekly periodicity, making it suitable for modeling using a hybrid forecasting model.

Based on the SARIMA-Holt-Winters hybrid forecasting method, the load of the Hasuhai service area from 2026 to 2045 was predicted. The load forecasting results for representative years are presented in Table 2, and the predicted growth trend is shown in Figure 2.

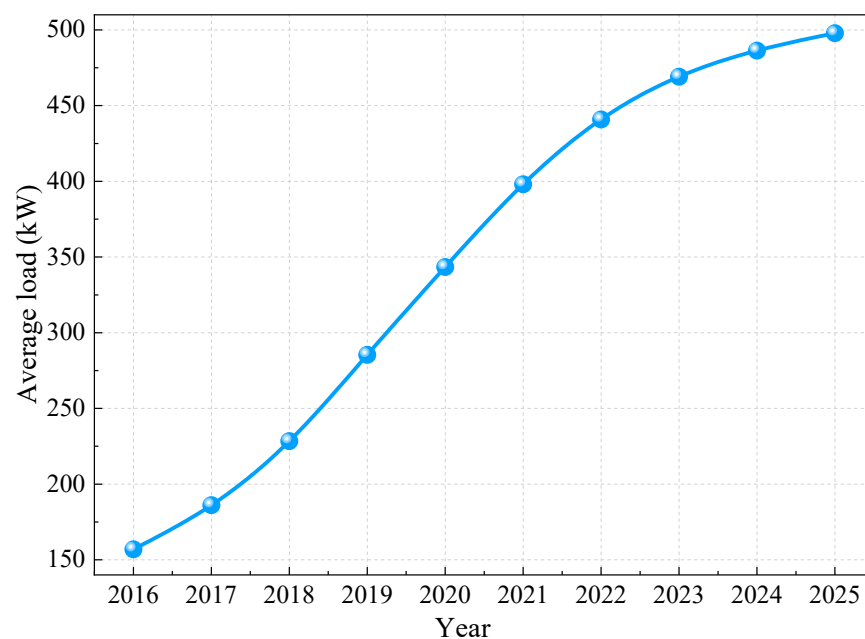


Figure 1. Historical annual average load variation trend of the Hasuhai service area from 2016 to 2025.

Table 2. Load forecasting results of the Hasuhai service area in representative years.

Year	Annual Average Load/kW	Annual Minimum Load/kW	Annual Maximum Load/kW
2026	551.85	514.15	587.66
2031	953.18	881.47	1020.84
2036	1739.69	1599.35	1872.64
2041	3442.93	3160.91	3741.18
2045	6195.53	5707.71	6660.26

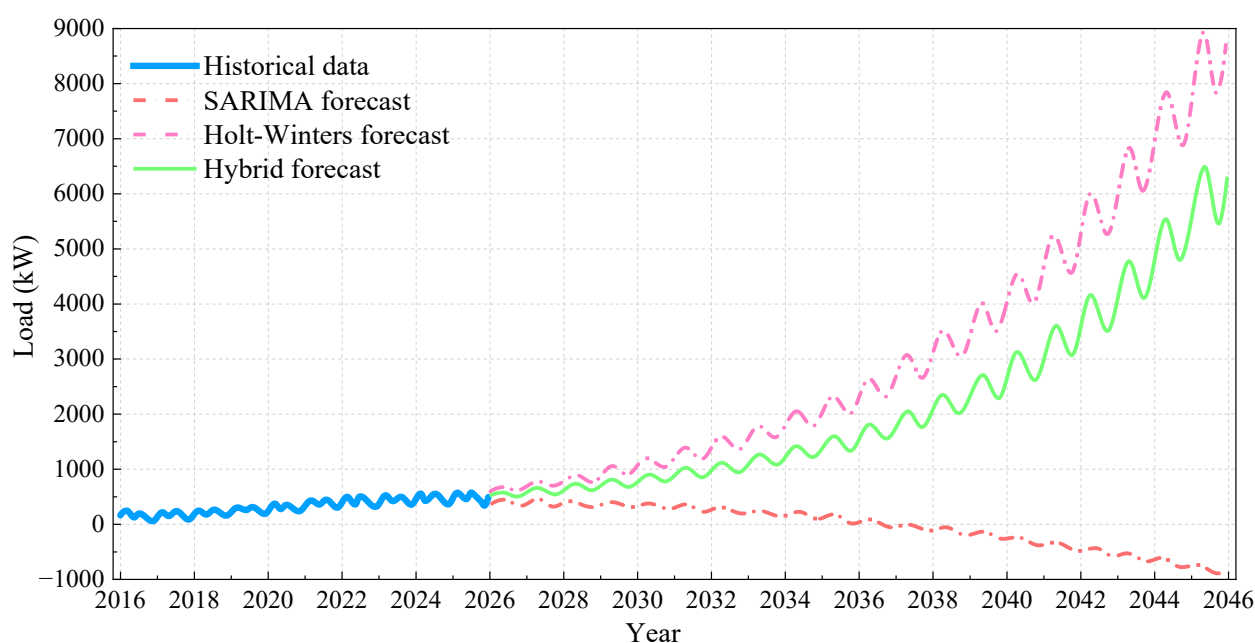


Figure 2. Predicted load growth trend of the Hasuhai service area from 2026 to 2045.

As shown in Table 2 and Figure 2, the future load of the service area is expected to exhibit a significant increasing trend. The average annual load increases from 551.85 kW

in 2026 to 6195.53 kW in 2045, corresponding to an approximately 11.22-fold increase. Meanwhile, the annual maximum load increases from 587.66 kW to 6660.26 kW, indicating that not only the total electricity demand of the service area will increase substantially, but also the peak charging pressure will be significantly intensified. From a staged perspective, the load increases rapidly during 2026–2032, further accelerates during 2033–2038, and enters a high-growth stage after 2039. This indicates that the large-scale development of new energy vehicles will continuously drive the increase in charging load demand in the service area.

To verify the rationality of the forecasting results, the hybrid model was validated using actual operating data from multiple perspectives, including seasonal index comparison, peak relative value comparison, and cumulative load deviation analysis. The results show that the predicted seasonal indices are highly correlated with the actual seasonal indices, the peak-load months can be accurately identified, and the relative deviation of cumulative load remains generally within approximately 5%. These results indicate that the hybrid model can effectively characterize both the seasonal fluctuations and long-term growth trend of the service area load.

To further quantify the forecasting accuracy, the historical load dataset was divided into a training set and a validation set. The data from 2016 to 2024 were used for model training, while the data from 2025 were used for out-of-sample validation. The calculated MAE, RMSE, and MAPE of the SARIMA-Holt-Winters hybrid model were 24.86 kW, 31.74 kW, and 4.38%, respectively. The MAPE remained below 5%, indicating that the hybrid model achieved acceptable forecasting accuracy for medium- and long-term planning-oriented analysis. Therefore, the forecasting results can provide reasonable load inputs for the subsequent staged capacity expansion and life-cycle economic assessment.

From the perspective of capacity planning, the rapid growth of future load will pose challenges to the long-term adaptability of the one-time construction scheme. These forecasting results provide the load basis for evaluating the baseline scheme and further optimizing the staged capacity expansion of the photovoltaic-storage-charging system.

3.2. Technical and Economic Performance of the Baseline Scheme

According to the initial scheme proposed by the project owner, the Hasuhai service area has been equipped with a 1.74 MW photovoltaic system, a 1200 kW/2400 kWh energy storage system, and 4900 kW of charging facilities. This scheme adopts a one-time construction mode and provides relatively strong power supply, energy storage regulation, and charging service capabilities in the initial stage. However, the continuous growth of future charging load was not fully considered in its capacity configuration. To evaluate its long-term adaptability, the scheme was analyzed in terms of photovoltaic power generation capability, energy storage regulation capability, supply–demand matching of charging facilities, economic performance, and environmental benefits. The results are presented in Table 3.

As shown in Table 3, the initial scheme exhibits favorable economic performance and a certain level of photovoltaic and energy storage support capability in the early stage of the project. Its NPV is 33.094 million CNY, the IRR is 25%, and the discounted payback period is 3.5 years, indicating strong short-term payback performance. However, as the charging load of the service area continues to increase, the fixed-capacity photovoltaic, energy storage, and charging facilities gradually become insufficient to meet long-term demand. In the long term, the photovoltaic self-sufficiency rate decreases to 4.6%, the energy storage regulation capability decreases to 1.4%, and the charger utilization rate increases to 126.4%. These results indicate a staged mismatch in which the scheme shifts from relatively sufficient capacity in the early stage to insufficient supply in the long term.

Therefore, the initial one-time construction scheme is more suitable for application scenarios with a short-term revenue orientation or relatively slow load growth. For service areas such as Hasuhai, where future charging demand is expected to increase rapidly, long-term service capacity requirements cannot be fully satisfied by relying solely on one-time capacity deployment. Multi-stage dynamic capacity expansion optimization is therefore required.

Table 3. Summary of technical matching and economic performance of the initial scheme.

Category	Key Indicator	Result	Assessment
PV generation	Installed capacity/first-year generation	1.74 MW/2.8024 GWh	Adequate in the initial stage
	25-year total generation	66.0239 GWh	Stable clean electricity can be provided
PV matching	PV self-sufficiency rate	57.9% → 4.6%	Long-term PV supply becomes insufficient
Energy storage	Regulation capability	18.2% → 1.4%	Long-term regulation capability weakens
Charging facilities	Supply–demand balance coefficient	8.88 → 0.79	Capacity shifts from redundancy to insufficiency
	Charger utilization rate/2045 peak demand	126.4%/15,489 kW	Long-term charging capacity is insufficient
Economic performance	NPV/IRR/discounted payback period/LCOC	33.094 million CNY/25%/3.5 years/0.210 CNY/kWh	Favorable short-term economics
Environmental benefits	25-year carbon reduction/NPV after carbon revenue	53,080 tCO ₂ /34.431 million CNY	Low-carbon benefits are achieved

3.3. Multi-Stage Capacity Expansion Results

To address the insufficient long-term adaptability of the initial scheme, the capacities of photovoltaic generation, energy storage, and charging facilities were optimized based on the multi-stage dynamic programming model using a strategy of “phased construction and dynamic expansion”. The planning horizon was set from 2026 to 2050 and was divided into five stages, with each stage covering five years. Among them, 2026–2045 was defined as the main period for load growth and capacity expansion, while 2046–2050 was regarded as the stable operation period. The staged capacity expansion scheme is presented in Table 4. Since the main expansion had been completed in the first four stages, no additional equipment capacity was added in the fifth stage, which was mainly used to evaluate the economic performance and continuous service capability of the existing system during the stable operation period.

Table 4. Staged capacity expansion scheme.

Stage	Time Span	Added PV Capacity/kW	Added ESS Capacity/Power	Added Charging Ports (Slow/Fast/Ultra-Fast; Total)	Added Charging Power/kW
Stage I	2026–2030	1440	527 kWh/132 kW	0/12/12; 24	3600
Stage II	2031–2035	760	776 kWh/194 kW	10/10/2; 22	2160
Stage III	2036–2040	0	1968 kWh/492 kW	22/22/5; 49	4860
Stage IV	2041–2045	0	2840 kWh/710 kW	24/24/6; 54	5400
Stage V	2046–2050	0	0	0/0/0; 0	0
Total	2026–2050	2200	6111 kWh/1528 kW	56/68/25; 149	16,020

As shown in Table 4, the major expansion of the multi-stage planning scheme is concentrated in the first four stages, and no new equipment capacity is added in the fifth stage. This indicates that the system scale formed during the first four stages is sufficient to support subsequent stable operation. The photovoltaic system is mainly expanded in the first two stages, with a cumulative added capacity of 2200 kW. The energy storage system is expanded progressively with load growth, eventually reaching a configuration of 6111 kWh/1528 kW. The charging facilities are expanded to 149 charging ports, with a total charging power of 16,020 kW.

From the perspective of expansion rhythm, the full capacity is not deployed at the initial stage. Instead, the equipment scale is gradually increased according to the load growth process. In the early stages, expansion is mainly intended to satisfy basic charging demand and clean electricity supply. In the middle and later stages, as the charging load increases rapidly, the energy storage capacity and the number of charging ports are substantially increased. This “moderate early-stage construction and rolling expansion in the middle and later stages” strategy can reduce the risk of early equipment idleness while improving service guarantee capability under long-term high-load conditions.

To further illustrate the operational robustness of the multi-stage scheme, a simplified holiday peak-load scenario was considered. According to the baseline evaluation, the projected peak charging demand in 2045 reaches 15,489 kW. In the initial scheme, the installed charging power is only 4900 kW, indicating that severe queuing or insufficient charging service capacity may occur during peak travel periods. In contrast, the multi-stage scheme forms a total charging power of 16,020 kW after phased expansion, which provides an installed power margin of approximately 531 kW, corresponding to about 3.4% of the projected 2045 peak demand. This indicates that the multi-stage scheme can basically satisfy the design peak-load requirement under the assumed long-term growth scenario.

During major holidays or temporary traffic surges, the system should adopt a coordinated operation strategy. Photovoltaic power should be locally consumed with priority, the energy storage system should discharge during peak charging periods to reduce grid pressure, and grid electricity should provide supplementary power when photovoltaic generation and storage discharge are insufficient. In addition, charging guidance, queue management, differentiated charging service, and temporary demand response can be used to mitigate short-term extreme peaks. If the observed holiday peak load continuously exceeds the design margin, the staged expansion model can be updated using newly collected operating data to trigger the next round of capacity expansion. Therefore, the proposed multi-stage scheme not only improves long-term capacity matching, but also provides a flexible operational basis for coping with sudden holiday peak-load events.

3.4. Life-Cycle Economic Performance and Sensitivity Results

From the perspective of life-cycle operation, the multi-stage planning scheme significantly improves the service capacity of the system and the utilization level of clean energy. During the planning horizon, the cumulative charging demand reaches 86.9 GWh, the cumulative photovoltaic power generation is approximately 77.72 GWh, and the clean energy self-sufficiency rate reaches 89.4%. These results indicate that the multi-stage scheme can make more effective use of photovoltaic generation and energy storage regulation capability, thereby alleviating the power supply pressure caused by long-term charging load growth.

To compare the comprehensive performance of the two construction modes, the economic performance, environmental benefits, and long-term adaptability of the initial and multi-stage schemes are compared in Table 5.

Table 5. Comprehensive comparison between the initial scheme and the multi-stage planning scheme.

Indicator	Initial Scheme	Multi-Stage Planning Scheme	Comparison Result
Present value of total investment	10.908 million CNY	15.200 million CNY	Higher investment is required for the multi-stage scheme
Present value of total O&M cost	1.489 million CNY	2.076 million CNY	The O&M scale is larger for the multi-stage scheme
Present value of total revenue	45.49 million CNY	74.62 million CNY	Higher revenue is obtained by the multi-stage scheme
NPV	33.094 million CNY	57.347 million CNY	The NPV is increased by 73.3% in the multi-stage scheme
IRR	25%	28%	The IRR is increased by 3 percentage points in the multi-stage scheme
Simple payback period	2.5 years	3.5 years	The initial scheme achieves faster capital recovery
Discounted payback period	3.5 years	4.5 years	The initial scheme achieves faster discounted capital recovery
LCOC	0.210 CNY/kWh	0.171 CNY/kWh	The LCOC is reduced by 18.6% in the multi-stage scheme
25-year carbon emission reduction	53,080 tCO ₂	62,490 tCO ₂	The carbon emission reduction is increased by 17.7% in the multi-stage scheme
Present value of carbon revenue	1.337 million CNY	1.573 million CNY	Higher carbon revenue is obtained by the multi-stage scheme
NPV after considering carbon revenue	34.431 million CNY	58.920 million CNY	Better economic performance is achieved by the multi-stage scheme
Clean energy supply capability	Long-term PV self-sufficiency rate: 4.6%	Life-cycle clean energy self-sufficiency rate: 89.4%	A higher level of clean energy utilization is achieved by the multi-stage scheme
Long-term energy storage regulation capability	1.4%	34.2%	Stronger regulation capability is provided by the multi-stage scheme
Overall assessment	Favorable short-term economic performance and faster payback	Higher long-term revenue and stronger adaptability	The multi-stage scheme is more suitable for high-load-growth scenarios

As shown in Table 5, although the present values of total investment and total operation and maintenance costs of the multi-stage planning scheme are higher than those of the initial scheme, its present value of total revenue, NPV, IRR, LCOC, carbon emission reduction, and long-term adaptability are all significantly improved. Compared with the initial scheme, the NPV of the multi-stage scheme increases by 73.3%, the IRR increases by 3 percentage points, and the LCOC decreases by 18.6%. This indicates that staged capacity expansion can achieve stronger long-term profitability and lower unit charging cost, although a higher investment is required.

In terms of environmental benefits, the 25-year cumulative carbon emission reduction in the multi-stage scheme reaches 62,490 tCO₂, which is 17.7% higher than that of the initial scheme. After carbon revenue is included, its NPV further increases to 58.920 million CNY. These results suggest that the dynamic expansion mode not only improves project economics but also enhances the low-carbon benefits of the photovoltaic-storage-charging system.

A benchmark comparison was further conducted between the calculated LCOC and the direct grid electricity purchase cost. Under the baseline grid electricity purchase price of 0.550 CNY/kWh, the LCOC of the multi-stage dynamic programming scheme is 0.171 CNY/kWh, which is approximately 68.9% lower than the direct grid electricity purchase price. The LCOC of the initial scheme is 0.210 CNY/kWh, which is also approximately 61.8% lower than the direct grid electricity purchase price. Although LCOC and grid electricity purchase price are not completely identical indicators, this comparison provides a useful benchmark for evaluating the economic competitiveness of the photovoltaic-storage-charging system. The results indicate that the proposed multi-stage scheme has a clear unit-cost advantage over direct electricity purchase without photovoltaic-storage coordination.

To analyze the effects of key external parameter variations on the economic performance of the multi-stage planning scheme, the grid electricity price, charging service fee, and discount rate were further selected for sensitivity analysis. The results are shown in Table 6.

Table 6. Sensitivity analysis results of the multi-stage scheme.

Sensitivity Factor	Variation Range	NPV Range/ 10^4 CNY	IRR Range/%	Main Effect
Grid electricity purchase price	0.495–0.605 CNY/kWh	5567.4–5902.0	27.5–28.5	Moderate effect
Charging service fee	0.45–0.55 CNY/kWh	5230.7–6238.7	25.0–31.0	Strongest effect
Discount rate	7.6–11.4%	4892.5–6720.8	28.0	Mainly affects NPV

Note: NPV values are expressed in 10^4 CNY. The baseline values of the grid electricity purchase price, charging service fee, and discount rate are 0.550 CNY/kWh, 0.50 CNY/kWh, and 9.5%, respectively.

As shown in Table 6, variations in the charging service fee have the most pronounced effects on NPV and IRR, followed by the grid electricity price, while the discount rate mainly affects the NPV level. Within the specified parameter variation ranges, the NPV of the multi-stage scheme remains positive, indicating that the scheme has favorable economic stability and risk resistance. In practical engineering applications, attention should therefore be paid to the effects of charging service fee policies, electricity price fluctuations, and financing cost changes on project revenue.

To further evaluate the combined influence of multiple uncertain factors, a preliminary Monte Carlo risk analysis was conducted based on the sensitivity ranges shown in Table 6. The grid electricity purchase price, charging service fee, and discount rate were treated as uncertain variables and were randomly sampled within their corresponding variation ranges. A total of 10,000 random scenarios were generated. The NPV of each scenario was estimated by linear interpolation based on the one-factor sensitivity results. The simulation results show that the mean NPV of the multi-stage scheme is approximately 57.70 million CNY, and the 5th–95th percentile interval is approximately 47.88–67.89 million CNY. The NPV remains positive in all sampled scenarios, indicating that the proposed multi-stage scheme maintains favorable economic feasibility under the combined uncertainty of electricity price, charging service fee, and discount rate.

It should be noted that this Monte Carlo analysis is intended as a preliminary risk assessment based on the available sensitivity results. In future work, more accurate probability distributions of load growth, electricity price fluctuations, charging behavior, financing costs, and equipment replacement costs should be obtained from long-term operating data to further improve the robustness of the risk assessment.

4. Discussion

This section further interprets the obtained results in terms of methodological contribution, long-term forecasting applicability, practical implementation constraints, safety considerations, and future research directions.

4.1. Methodological Contribution and Comparison with Previous Studies

As can be seen from Tables 5 and 6, clear differences exist between the initial one-time construction scheme and the multi-stage dynamic programming scheme in terms of investment intensity, capital recovery speed, long-term profitability, and long-term adaptability. The initial scheme involves a smaller investment scale, a shorter payback period, and a relatively simple construction and management process. Therefore, it is more suitable for scenarios with a strong short-term revenue orientation, conservative load growth expectations, or strict requirements for capital recovery. However, its main limitation lies in the lack of dynamic adaptability in capacity configuration. As the charging load continues to increase, the photovoltaic self-sufficiency rate, energy storage regulation capability, and charging facility supply capacity all decrease significantly, making it difficult to satisfy peak charging demand in the long term.

The multi-stage dynamic programming scheme is more suitable for service areas characterized by rapid load growth, long-term operational revenue orientation, and higher requirements for low-carbon development. Through staged capacity expansion, the capacities of photovoltaic generation, energy storage, and charging facilities are gradually increased in accordance with load growth, thereby effectively avoiding early-stage resource idleness and long-term service capacity shortages associated with the one-time construction mode. The results show that the multi-stage scheme outperforms the initial scheme in terms of NPV, IRR, LCOC, carbon emission reduction benefits, and long-term adaptability.

4.2. Applicability and Uncertainty of Long-Term Load Forecasting

The long-term forecasting horizon introduces unavoidable uncertainty because future transportation technologies, charging behavior, electricity prices, vehicle energy efficiency, and socioeconomic development may change over time. Therefore, the forecasting results in this study should be interpreted as planning-oriented load scenarios rather than deterministic predictions of future daily loads. The 2026–2045 forecasting period was selected to characterize the long-term load growth trend and determine the staged capacity expansion requirements of the expressway service area. Therefore, the predicted results are mainly used as planning inputs for capacity optimization rather than precise descriptions of future daily load variations. The period from 2046 to 2050 is further used as a stable operation period for evaluating the life-cycle economic performance and continuous service capability of the expanded system.

The SARIMA-Holt-Winters hybrid model was adopted because the load series of an expressway service area contains both long-term trend evolution and periodic fluctuations. The Holt-Winters component is used to describe the long-term growth tendency of the load series, while the SARIMA component is used to correct seasonal and weekly periodic variations. Compared with a single statistical model, this hybrid structure provides a more suitable forecasting framework for planning-oriented analysis under limited site-level data conditions. In addition, the model was validated using historical operating data, and the MAPE of the validation period remained below 5%, indicating that the forecasting results can provide acceptable load inputs for staged capacity planning.

It should also be noted that the historical load data of the Hasuhai service area are not independent of socioeconomic development. The observed load growth during 2016–2025 already reflects the combined effects of regional traffic demand, service-area

function expansion, tourism and logistics activities, electric vehicle penetration, and charging infrastructure development. Therefore, the site-level load series can be regarded as an integrated response to both local operation characteristics and broader socioeconomic changes. Meanwhile, national and regional development trends were considered qualitatively in interpreting the forecasting results. The rapid growth of new energy vehicle ownership and charging infrastructure in China provides an important background for the projected increase in expressway charging demand.

Long-term forecasting over extended planning horizons remains subject to considerable uncertainty due to potential changes in transportation technologies, charging behaviors, electricity market conditions, and regional socioeconomic development. In practical applications, the proposed multi-stage dynamic planning framework should therefore be combined with a rolling-update mechanism. Newly collected information, including traffic flow characteristics, charging demand, equipment utilization, electricity price variations, and policy changes, can be continuously incorporated into the forecasting model. Accordingly, the staged capacity expansion strategy can be dynamically adjusted according to actual development conditions, thereby reducing the risk associated with long-term technological and socioeconomic uncertainties.

4.3. Practical Applicability: Wind Energy, Fire Safety, and LCA/LCSA Implications

Although Inner Mongolia has abundant wind energy resources, wind power was not included in the present system boundary. This study focuses on the staged expansion of an existing photovoltaic-storage ultra-fast charging station in the Hasuhai expressway service area. At the scale of an expressway service area, wind turbine deployment may be constrained by available land, safety distance, noise, visual impact, operation and maintenance complexity, and grid-connection approval. In addition, the initial system proposed by the project owner already includes photovoltaic generation, energy storage, and charging facilities; therefore, the present study was designed to evaluate and optimize this existing photovoltaic-storage-charging system rather than to redesign the entire renewable energy supply structure. Nevertheless, a wind-photovoltaic-storage-charging hybrid system may further improve renewable energy complementarity and should be investigated in future work.

Fire safety should also be considered in the practical implementation of photovoltaic-storage-charging systems, particularly when these systems are located near fuel stations, service buildings, parking areas, or other densely used service facilities. Potential fire-related risks include battery thermal runaway in the energy storage system, electrical faults in charging facilities, and direct-current faults on the photovoltaic side. Therefore, engineering design should include early fire detection, emergency shutdown, electrical isolation, thermal runaway isolation, fire compartments, ventilation control, and appropriate extinguishing systems selected according to the equipment type and local fire safety requirements. Fire risk should not be regarded only as an economic cost; it is also a safety and operational reliability issue that directly affects the applicability of the system in expressway service areas.

From an economic and environmental perspective, fire events may influence the life-cycle assessment results through several pathways. First, fire protection systems increase the initial investment and operation and maintenance costs. Second, equipment damage and business downtime may reduce charging revenue and increase replacement costs. Third, fire events may lead to additional carbon emissions due to equipment replacement, emergency response, and temporary reliance on grid electricity during system downtime. Therefore, fire-safety cost modeling and probabilistic downtime assessment should be incorporated into future economic evaluation frameworks. Monte Carlo simulation can

be used in future studies to characterize the uncertainty of fire-related downtime costs, equipment replacement costs, and their effects on NPV and LCOC.

In terms of life-cycle assessment, LCA mainly focuses on environmental impacts, whereas life-cycle sustainability assessment (LCSA) extends the assessment boundary to environmental, economic, and social dimensions. The present study considers life-cycle economic performance and carbon emission reduction benefits, but it does not constitute a complete LCSA. Future studies should further include fire safety, social acceptance, land-use impact, equipment recycling, operational resilience, and wind-photovoltaic-storage complementarity to establish a more comprehensive sustainability evaluation framework for expressway service area energy systems.

4.4. Limitations and Future Research

It should also be noted that the multi-stage scheme imposes higher requirements on project implementation and management. Since phased construction, rolling adjustment, and continuous optimization are required, actual traffic flow, charging demand, equipment utilization, and electricity price policies in the service area should be continuously monitored during project implementation. In practical engineering applications, a strategy of “moderately advanced deployment and phased expansion” can be adopted. Specifically, excessive one-time configuration should be avoided in the early stage, while near-term load demand and necessary redundancy should be prioritized. In the middle and later stages, dynamic expansion should be conducted based on actual load growth and equipment operation conditions, so that a balance can be achieved between investment control and long-term adaptability.

Overall, for expressway service areas with significant future charging load growth, such as the Hasuhai service area, the multi-stage dynamic programming scheme shows stronger long-term adaptability and greater comprehensive benefits than the one-time construction scheme.

Future work should further incorporate dynamic daily operation, holiday peak-load scenarios, wind-power integration, Monte Carlo risk simulation, fire-safety cost modeling, and a complete life-cycle sustainability assessment. These extensions would improve the robustness and practical applicability of the proposed planning framework.

5. Conclusions

The main conclusions of this study are as follows:

- (1) The electricity load of the Hasuhai expressway service area is projected to increase significantly during the planning period. The annual average load is projected to increase from 551.85 kW in 2026 to 6195.53 kW in 2045, corresponding to an approximately 11.22-fold increase. This indicates that the future charging demand of expressway service areas may increase rapidly under the large-scale development of electric vehicles.
- (2) The initial one-time construction scheme shows favorable short-term economic performance but insufficient long-term adaptability. Although the initial scheme achieves an NPV of 33.094 million CNY, an IRR of 25%, and a discounted payback period of 3.5 years, its long-term photovoltaic self-sufficiency rate and energy storage regulation capability decrease to 4.6% and 1.4%, respectively, while the charger utilization rate increases to 126.4%. These results indicate a staged mismatch between fixed capacity configuration and continuously increasing charging demand.
- (3) The multi-stage planning scheme improves the dynamic matching between system capacity and load growth. Through phased expansion, the photovoltaic capacity is increased to 2200 kW, the energy storage system reaches 6111 kWh/1528 kW, and

149 charging ports with a total charging power of 16,020 kW are formed. This strategy reduces the risk of early-stage equipment idleness and improves long-term service capacity under high-load conditions.

- (4) The multi-stage planning scheme provides better long-term economic and environmental benefits than the initial scheme. Compared with the initial scheme, the NPV increases from 33.094 million CNY to 57.347 million CNY, the IRR increases from 25% to 28%, the LCOC decreases from 0.210 CNY/kWh to 0.171 CNY/kWh, and the 25-year carbon emission reduction increases from 53,080 tCO₂ to 62,490 tCO₂. Sensitivity analysis further shows that the charging service fee is the most influential factor affecting project economics, followed by the grid electricity price and discount rate. The preliminary Monte Carlo risk analysis further indicates that the NPV remains positive under the combined uncertainty of these economic parameters.

Overall, the proposed multi-stage planning framework is more suitable for expressway service areas with rapidly increasing charging demand. In future work, dynamic daily operation, holiday peak-load scenarios, wind-power integration, fire-safety cost modeling, Monte Carlo risk assessment, and complete life-cycle sustainability assessment should be further incorporated.

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