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Demand Forecasting and Allocation Optimization of Green Power Grid Supply Chain Based on Machine Learning Algorithm: A Study Based on the Whole-Process Data of Power Grid Materials

Hanyu Rao ^{1,†}, Jiancheng Li ^{2,†} and Xiaojun Sun ^{3,*}

¹ Carey Business School, Johns Hopkins University, 555 Pennsylvania Avenue, Washington, DC 20001, USA; hrao4@jh.edu

² School of Economics, Sichuan University, Chengdu 610065, China; lijiancheng@stu.scu.edu.cn

³ School of Foreign Languages, Hubei University of Economics, Wuhan 430205, China

* Correspondence: sunxiaojun@hbue.edu.cn

† These authors contributed equally to this work.

Abstract: The efficient management of the green power grid supply chain is of great significance in addressing global energy transformation and achieving sustainable development goals. However, traditional methods struggle to effectively cope with the complexity and dynamics of demand forecasting and the multi-objective optimization problems in material allocation. In response to this challenge, this paper proposes a machine-learning-based demand forecasting and allocation optimization method, aiming to improve the management efficiency of the supply chain and reduce environmental impacts. First, based on the whole-process data of power grid materials, a multi-model fusion strategy is adopted for demand forecasting. By combining machine learning models such as long short-term memory (LSTM), extreme gradient boosting (XGBoost), and random forest, the prediction accuracy and the generalization ability of the model are significantly improved. Moreover, a “distributed collaborative optimization algorithm” is proposed. By decomposing the power grid regions, this paper optimizes transportation routes and inventory management, and comprehensively reduces transportation, inventory, and environmental protection costs while taking into account the real-time requirements in a complex supply chain environment. Finally, an empirical analysis is carried out in combination with the optimized allocation plan, verifying the practical effectiveness of the proposed method. The results indicate that the optimized scheme significantly outperforms the traditional method in terms of total cost, transportation efficiency, and carbon emissions. Specifically, the optimized scheme achieves a 13% reduction in transportation costs, a 10% decrease in inventory costs, and a 25% cut in environmental protection expenses. Additionally, it decreases transportation-related carbon emissions by approximately 250 tons. The demand forecasting and allocation optimization method based on machine learning has obvious economic and environmental advantages in the green power grid material supply chain. By effectively integrating various algorithms, this paper enhances the accuracy and stability of material management while substantially reducing operating costs and carbon emissions. This is in line with the sustainable goals of green power grid development. The paper provides an optimized framework with practical value for managing the green supply chain in the power grid industry.

Keywords: green power grid; supply chain optimization; demand forecasting; machine learning; environmental effect



Academic Editor: Paulo Santos

Received: 17 December 2024

Revised: 20 January 2025

Accepted: 27 January 2025

Published: 4 February 2025

Citation: Rao, H.; Li, J.; Sun, X. Demand Forecasting and Allocation Optimization of Green Power Grid Supply Chain Based on Machine Learning Algorithm: A Study Based on the Whole-Process Data of Power Grid Materials. *Sustainability* **2025**, *17*, 1247. <https://doi.org/10.3390/su17031247>

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1. Introduction

As global energy transformation and climate change challenges become increasingly urgent, the green grid, one of the key technologies for optimizing energy structures and promoting sustainable development, has emerged as a crucial component of energy policies worldwide. The construction of a green power grid requires not only an efficient and intelligent power transmission system but also a strong emphasis on environmental protection and resource conservation during its operation [1]. As a vital element in the development of green power grids, power grid supply chain management plays a significant role in optimizing resource allocation, enhancing operational efficiency, and reducing carbon emissions. However, the current power grid material supply chain faces several challenges, including inaccurate material demand forecasting, inefficient material allocation, and inadequate inventory management. These issues directly impact the operational efficiency of the power grid and hinder the achievement of environmental protection goals [2,3].

Material management within the power grid supply chain, which spans the entire process from procurement to storage, allocation, and transportation, is foundational to the grid's efficiency. As the scale of power grids continues to expand, the volatility and complexity of material demand are also increasing [4]. Accurately predicting material demand and efficiently managing transportation and inventory have become critical to enhancing the performance of the power grid supply chain and minimizing its environmental impact. Despite the widespread application of machine learning (ML) and deep learning methods in power grid material demand forecasting in recent years, some studies still rely on traditional statistical models or experience-driven forecasting methods. For instance, many studies continue to use linear statistical approaches, such as the autoregressive integrated moving average (ARIMA) model. While these methods perform well in handling univariate time series trends, their forecasting accuracy significantly drops when faced with multi-factor coupling and nonlinear demand variations [5]. Additionally, traditional statistical models often assume data stationarity, an assumption that is difficult to hold in the complex and dynamic demand scenarios of power grid supply chains [6]. Similarly, experience-based linear programming (LP) models also face limitations in allocation optimization, such as insufficient support for dynamic adjustments and multi-objective optimization. These issues highlight the shortcomings of traditional methods in addressing complex, multidimensional, and dynamic demand.

Some studies have introduced ML techniques, including long short-term memory (LSTM) and extreme gradient boosting (XGBoost), to improve forecasting accuracy. However, challenges like insufficient data, improper feature selection, and overfitting of prediction models remain. For example, when ML models encounter high-dimensional, dynamic nonlinear data, they may experience significant forecasting bias due to a lack of sufficient data preprocessing and feature extraction [7]. Moreover, most existing studies have not fully integrated real-time feedback mechanisms for dispatching, making it difficult to respond to demand changes during unexpected events [8]. Although existing ML methods have made breakthroughs in forecasting accuracy, further research is needed in areas such as data timeliness and multi-objective collaborative optimization. Based on the current research landscape, developing and introducing more precise and efficient demand forecasting and dispatching optimization methods has become a key factor in enhancing the efficiency of green grid supply chains. This is particularly true for methods that combine ML techniques with dynamic feedback mechanisms.

ML algorithms can automatically mine rules from a large number of historical data, accurately predict the demand, and optimize the material allocation scheme in real time. For example, research in green energy supply chains has shown that deep learning models can significantly improve demand forecasting accuracy and provide reliable data support for

resource optimization and allocation [9]. Additionally, the XGBoost algorithm, based on ensemble learning, has been proven to perform excellently when handling high-dimensional and non-stationary data [10]. These methods not only enhance forecasting accuracy but also reduce transportation distances and carbon emissions by optimizing dispatching plans, which is of great significance for achieving the United Nations Sustainable Development Goals. In the context of green grid supply chains, ML techniques can effectively address issues such as demand fluctuations, data complexity, and multi-factor coupling, thereby driving dual improvements in supply chain efficiency and environmental benefits.

The structure of this paper is as follows. Section 2 is the literature review, which reviews and analyzes the progress in related research of power grid supply chain management, demand forecasting, and allocation optimization. Section 3 introduces the research methods in detail, including data preprocessing, demand forecasting model design, and allocation optimization algorithm construction. Section 4 shows the experimental results and analysis, and compares the prediction accuracy and optimization effects of different methods. Section 5 discusses the main research findings and their practical significance. Section 6 is the conclusion, which summarizes the research results and looks forward to suggest future research directions. The innovation of this paper is that an ML fusion method based on the whole-process data of power grid materials is proposed. This method integrates various ML models and improves the accuracy and stability of power grid material demand forecasting.

2. Literature Review

2.1. Research Status of Green Supply Chain Management (GSCM)

GSCM has become a focal point of attention in both academic and industrial circles in recent years. Green supply chains are of significant importance in terms of environmental protection, resource conservation, and economic benefits. The power grid material supply chain, as a key component of the green supply chain, is characterized by large demand fluctuations, a wide variety of materials, and high time sensitivity. Traditional supply chain management methods are no longer sufficient to meet increasingly complex environmental demands. For example, Deng et al. [11] assessed the low-carbon economic resilience of coal-resource-based cities using artificial intelligence. They found that high-tech industries played an important role in resource optimization and environmental protection, which provided valuable insights for green dispatching in the power grid supply chain.

In recent years, the application of data platforms has significantly enhanced the management capabilities of green supply chains. For instance, Wang et al. [12] proposed a “5 W” analytical framework based on data platform management, which significantly improved supply chain management efficiency through detailed data analysis. This method provides a reference for the intelligent management of the power grid material supply chain. However, research on the power grid material supply chain remains fragmented and lacks a systematic analytical framework.

2.2. Research Progress in Demand Forecasting and Allocation Optimization Methods

In the power grid material supply chain, demand forecasting and allocation optimization are critical for improving supply chain efficiency. Traditional demand forecasting methods, such as ARIMA and linear regression, perform well in processing univariate time series data but often fall short in multi-dimensional dynamic demand scenarios. For example, Yu et al. [13] studied the impact of environmental policies on corporate emissions. They found that models based on a single variable could not capture complex demand changes, and this shortcoming was especially evident in dynamic power grid supply chains.

The introduction of ML techniques in recent years has significantly improved the accuracy and stability of demand forecasting. For example, Li et al. [14] investigated the impact of climate change on corporate resource allocation and management. They also highlighted that ML models had unique advantages in capturing nonlinear data features, particularly in situations involving resource misallocation and dynamic demand changes. Similarly, Li et al. [15] used a differential method for evaluation in their research on low-carbon cities, and found that ML methods could significantly improve the adaptability of demand forecasting.

2.3. Power Grid Material Management

Power grid material management involves multiple stages, including procurement, storage, transportation, and dispatching, and its management efficiency directly affects the safety and reliability of power grid operations. In recent years, the widespread application of the Internet of Things and big data technologies has provided significant support for the fine-tuning of power grid material management. In terms of resource allocation and clean energy development, Li et al. [16] demonstrated the sustainable development paths driven by big data through case studies, and offered theoretical support for the power grid material supply chain. Additionally, Li et al. [17] studied the impact of climate change on corporate environmental, social, and governance performance. They found that rational resource allocation could effectively mitigate the negative effects of climate change, which provided a valuable reference for dispatching within the power grid material supply chain.

2.4. Summary

Although significant progress has been made in recent years regarding research on GSCM, demand forecasting, and optimization of distribution, most of these studies have focused on specific technologies. There is still a lack of systematic solutions for the complex, multi-objective scenarios in the material supply chains of power grids. Therefore, future research needs to further integrate multiple technological approaches and construct a more intelligent and systematic framework for power grid material management.

3. Research Method of Supply Chain Demand Forecasting and Allocation Optimization for the Green Power Grid

3.1. Research Framework

To effectively address the challenges of demand forecasting and allocation optimization in the green power grid supply chain, this paper introduces an innovative “dual-track parallel + dynamic feedback” framework. This framework separates demand forecasting and allocation optimization into distinct research modules, while enabling real-time interaction between them through a dynamic feedback mechanism. This approach enhances both the accuracy and applicability of the model, as illustrated in Figure 1.

Figure 1 reveals that the demand forecasting and allocation optimization processes operate as two parallel, independent tracks. The demand forecasting module is dedicated to developing a high-precision model that incorporates historical data and various influencing factors, and generating accurate estimates of material demand. Meanwhile, the allocation optimization module leverages these forecasted results to optimize resource distribution, ensuring efficient supply chain allocation. Both modules are synchronized through a data interface, ensuring the relevance and effectiveness of the optimization process. To enhance the system’s adaptability, a dynamic feedback mechanism is introduced based on the dual-track parallel structure. This mechanism facilitates real-time data collection and model iteration, allowing actual allocation outcomes and forecasting errors to feed back into the demand forecasting module, thereby improving its predictive accuracy. Simultaneously,

the optimization results are adjusted in response to the updated forecast data, creating a closed-loop feedback system.

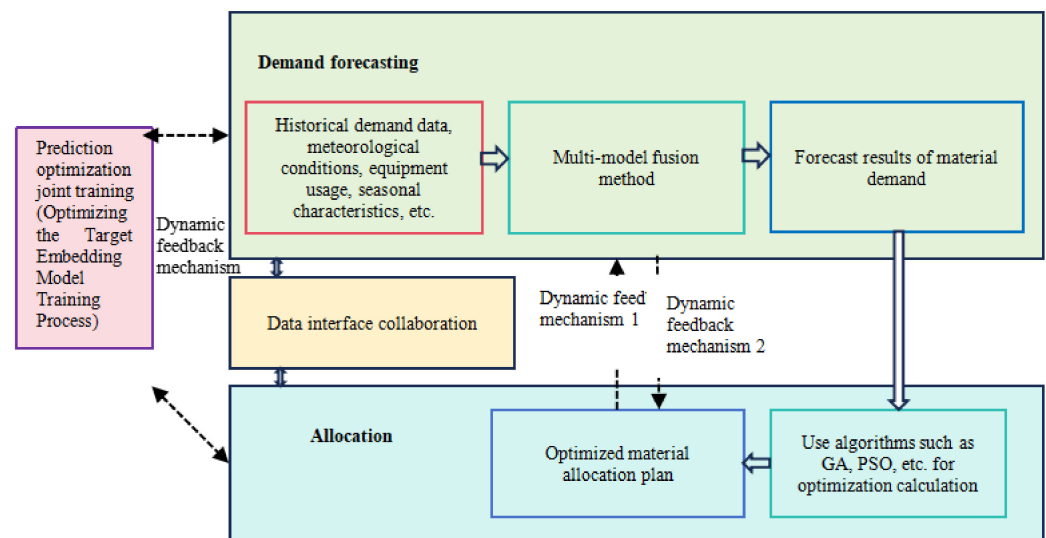


Figure 1. The “dual-track parallel + dynamic feedback” research framework for green grid supply chain demand forecasting and distribution optimization.

In the “dual-track parallel + dynamic feedback” framework, a “decision-centric learning framework” is further introduced. It directly integrates the objective function of allocation optimization into the loss function of the demand forecasting model, enabling joint training of both prediction and optimization. With this approach, model training not only focuses on forecasting accuracy but also optimizes the final decision-making outcomes. The new optimization objective is represented by the joint loss function, as shown in Equation (1):

$$L_{\text{joint}} = \alpha L_{\text{forecast}} + \beta L_{\text{decision}} \quad (1)$$

L_{forecast} represents the forecasting error, and L_{decision} denotes the optimization decision bias generated based on the forecasted values. α and β are weight parameters used to balance the forecasting and decision-making objectives.

3.2. Data Source and Preprocessing

The data primarily originate from the material management system and related auxiliary data platforms of a national power grid enterprise. The material management system data encompass various types of materials, including power equipment, consumables, spare parts, and over 500 distinct materials. The time span covers five years of historical data, updated daily, with time series extending beyond 1825 entries. Geographically, the data span 31 provincial regions of China, encompassing more than 300 warehouses and distribution points. The logistics system data include real-time records of transportation routes, tools, and time, with over 2 million records. External environmental data capture factors such as weather conditions and changes in energy policies, collected monthly and consisting of approximately 50,000 records. In total, the dataset amounts to around 300 gigabytes (GB), comprising both structured and unstructured data. Structured tabular data make up about 70%, and unstructured text data account for roughly 30%.

The demand for bulk materials, such as power equipment, exhibits clear seasonality, particularly influenced by factors like the increase in air conditioning load during summer months. The demand for low-value consumables is frequent but highly volatile, leading to significant fluctuations. As a result, the data distribution is uneven. Some material demands are closely linked to power grid load and weather conditions. For instance,

heavy rainfall may drive increased demand for cables, reflecting strong time-dependent correlations in the data. Additionally, material demand demonstrates a clear hierarchical structure, with nested relationships observed at national, provincial, and municipal levels of the power grid.

To ensure the efficient analysis of large-scale, complex data, several data processing steps are undertaken. Initially, data cleaning is performed, which includes addressing duplicate records. Using unique identifiers, such as material numbers, duplicates are eliminated, reducing redundant entries. For unstructured data, natural language processing (NLP) techniques are employed to extract key fields from logistics logs [18]. Next, the handling of missing values is addressed. Missing data account for approximately 5% of the dataset, and this problem is treated through various methods. For missing values in time series data, regularization interpolation (specifically quadratic spline interpolation) is applied [19]. For missing values in classified data, the random forest (RF) classifier is used to predict and fill in the gaps. Outlier detection involves identifying and removing invalid data, achieved by combining the isolation forest algorithm with critical features such as power grid transportation time and inventory levels. In the feature engineering process, a feature combination approach is utilized to construct composite features and reduce dimensionality. Principal component analysis (PCA) is applied to high-dimensional feature data. It reduces the number of features from 50 to around 10 while retaining 99% of the original information.

Given the characteristics of the data, a multi-dimensional hierarchical strategy is adopted to optimize their organization. By material type, high-value materials (transformers and line equipment) and frequently used consumables (joint materials) are modeled separately. By time dimension, data are decomposed into short-term (monthly), medium-term (quarterly), and long-term (annual) demand levels to address optimization needs across different time scales. In terms of spatial dimension, a hierarchical model is built based on administrative regions and power grid partitions. Transportation and warehousing are optimized according to regional variations. Finally, by business process, the data are divided into four sub-layers: procurement, transportation, inventory, and usage, with each layer processed and analyzed independently to generate modular inputs.

To verify the quality of the processed data, the following evaluation metrics are used. Integrity: The proportion of missing values has dropped below 0.1%. Consistency: The data redundancy ratio is reduced to 0.05%. Validity: The proportion of outliers is less than 1%.

3.3. The Design of a Demand Forecasting Model

Here, LSTM, gradient boosting decision tree, and RF are selected for multi-model fusion. The reasons are as follows: LSTM is particularly effective at capturing long-term dependencies in time series data, making it ideal for scenarios where power grid material demand fluctuates seasonally. XGBoost excels at processing non-time-series features, such as meteorological conditions and policy changes. It is highly sensitive to these factors, efficiently handling high-dimensional sparse data and identifying key features [20]. RF offers exceptional robustness, making it well-suited for handling data with significant nonlinear relationships. This capability enhances the model's generalization ability, allowing it to perform effectively across diverse data scenarios.

Specifically, LSTM performs exceptionally well in handling time series data, particularly in capturing long-term dependencies. In the green grid supply chain, material demand is often influenced by seasonal variations and historical trends. For example, the surge in air conditioning use during the summer significantly increases equipment demand, and these long-term fluctuations cannot be accurately captured by traditional statistical methods. The gating mechanisms in LSTM (such as input, forget, and output gates) ef-

fectively filter and retain critical information during prediction, making it well-suited for complex time-dependent demand scenarios. XGBoost has a notable advantage in handling high-dimensional non-time-series feature data. For instance, external environmental data in the power grid supply chain, such as meteorological conditions and energy policies, and regional characteristics like load levels and economic development, are high-dimensional and sparse. XGBoost not only reduces redundant data through automated feature selection, but also prevents overfitting through its regularization mechanism, providing stronger generalization capabilities for predictive models. The randomness and high robustness of RF make it well-suited for handling complex data with significant nonlinear relationships. In the green grid context, material demand may be influenced by numerous nonlinear factors, such as interactions between weather changes and equipment wear. By constructing multiple decision trees and averaging their results, RF mitigates the bias of individual models, enhancing the stability and accuracy of the overall prediction model.

According to the actual demand of a green power grid supply chain, the following multidimensional factors are integrated as input variables. Historical demand data: material demand in the most recent three years and its changing trend. Meteorological conditions: variables such as temperature, humidity and wind speed, with particular emphasis on the impact of extreme weather events on demand. Service life of equipment: predicted demand for equipment replacement, based on a life expectancy model. Regional characteristics: factors like regional power grid load and the level of economic development.

This paper proposes an enhanced weighted stacking method designed to improve overall prediction accuracy by combining the outputs of LSTM, XGBoost, and RF models. In the first layer, each base model is independently trained, and its prediction results are generated. In the second layer, a meta-learning model is used to construct a weight distribution for the base models.

In order to improve the prediction accuracy and generalization ability of the model, the following optimization strategies are adopted:

Bayesian optimization is used to optimize the hyperparameters. A Gaussian process is applied to build a proxy model to quickly find the optimized combination of hyperparameters and avoid the computational overhead of a traditional grid search.

A multi-objective loss function is introduced, which considers both prediction accuracy and generalization ability, as shown in Equation (2):

$$\mathcal{L} = \alpha \cdot \mathcal{L}_{\text{error}} + \beta \cdot \mathcal{L}_{\text{complexity}} \quad (2)$$

$\mathcal{L}_{\text{error}}$ indicates the traditional mean squared error (MSE), which reduces the prediction error. $\mathcal{L}_{\text{complexity}}$ represents the regular term of model complexity to prevent over-fitting, specifically as Equation (3):

$$\mathcal{L}_{\text{complexity}} = \sum_{i=1}^k \|\theta_i\|^2 \quad (3)$$

The weight coefficients α and β are adjusted according to the task requirements.

Data augmentation is applied to generate a diverse set of training samples, thereby enhancing the model's robustness through sliding window segmentation of time series. K-fold cross-validation is employed to evaluate the model performance and ensure the stability of the results.

This paper designs three weight configuration experiments to validate the superiority of the dynamic weight adjustment method. Uniform weights: the weights for all base models are set as $w_i = 1/k$; fixed weights: fixed weights are assigned based on empirical values $w_i = \{0.4, 0.3, 0.3\}$ (weights for LSTM, XGBoost, and RF are 0.4, 0.3, and 0.3, respectively); dynamic weight adjustment: the proposed dynamic weight adjustment equation is applied.

The performance of these weight configuration methods is evaluated using the following metrics: MSE measures prediction accuracy; stability index (SI) assesses the sensitivity of the prediction results to different datasets, with smaller values indicating more stable predictions. Table 1 presents the results.

Table 1. Prediction performance evaluation results of different weight configuration methods in the weighted stacking model.

Weight Configuration Method	MSE (the Smaller, the Better)	SI (the Smaller, the Better)
Uniform Weights	198.3	0.042
Fixed Weights	185.7	0.035
Dynamic Weight Adjustment (This Paper)	172.4	0.021

Based on Table 1, the dynamic weight adjustment method achieves an MSE of 172.4, significantly outperforming both the uniform and fixed weight methods. This indicates that dynamic weight adjustment better leverages the strengths of the base models, reducing overall prediction errors. The SI of the dynamic weight adjustment method is 0.021, which is lower than both the fixed and uniform weight methods. This suggests that dynamic weight adjustment effectively balances the prediction bias of the base models, improving the stability of the prediction results across different datasets. Through experimental validation of the weight configuration for the weighted stacking method, the dynamic weight adjustment approach demonstrates superior performance in both prediction accuracy and stability. Compared to the uniform and fixed weight methods, the proposed weight configuration method is more adaptable and advantageous. It provides both theoretical and practical support for the efficient application of the weighted stacking model.

3.4. Construction of Allocation Optimization Model

3.4.1. Optimization Objectives and Constraints

In green power grid supply chain management, allocation optimization is a critical component. Its primary objective is to minimize overall costs while meeting the operational constraints of the power grid through strategic resource scheduling and path planning.

The heart of allocation optimization lies in developing a model that minimizes total cost. This cost comprises three key components: (1) transportation cost (C_t) is related to transportation distance, material weight, and vehicle type; (2) inventory cost (C_i) is affected by storage capacity and inventory turnover rate; and (3) environmental protection cost (C_e) is linked to carbon emissions and environmental protection indicators. The specific equations are shown below:

$$C_t = \sum_{r \in R} d_r \cdot w_r \cdot \rho_r \quad (4)$$

d_r is the transportation distance, w_r is the material weight, and ρ_r is the unit transportation cost.

$$C_i = \sum_{k \in K} h_k \cdot s_k \quad (5)$$

h_k is the unit inventory cost, and s_k is the inventory.

$$C_e = \sum_{p \in P} \sigma_p \cdot e_p \quad (6)$$

σ_p is carbon emission, and e_p is the emission cost coefficient.

The constraints are as follows. Power grid operation safety constraint: The material supply shall meet the power grid operation safety standard to ensure that the equipment is supplied on demand, as shown in Equation (7):

$$S_{t,i} \geq D_{t,i} \forall t, i \quad (7)$$

$S_{t,i}$ is the supply, and $D_{t,i}$ is the demand.

Material timeliness constraint: The delivery time should meet the timeliness requirements of power grid maintenance or construction, as shown in Equation (8):

$$T_r \leq T_{max} \forall r \quad (8)$$

T_r is the delivery time, and T_{max} is the maximum allowable time.

Environmental protection index limit: The carbon emission of transportation and inventory activities shall be lower than the specified threshold, as shown in Equation (9):

$$\sum_{p \in P} \sigma_p \leq \sigma_{max} \quad (9)$$

3.4.2. Algorithm Innovation

The improvement based on GA addresses a common limitation. While GA excels at global search, it is prone to getting stuck in local optima during the later stages of convergence. To mitigate this issue, an adaptive mutation strategy is introduced, which dynamically adjusts the mutation probability to maintain population diversity, as demonstrated in Equation (10):

$$P_{mut} = \frac{1}{1+} e^{-k(g_{max}-g)} \quad (10)$$

P_{mut} is the mutation probability, g is the current algebra, g_{max} is the largest algebra, and k is the adjustment coefficient.

GA is a global optimization algorithm based on natural selection and genetic mechanisms, particularly well-suited for solving nonlinear and multi-objective optimization problems. In the context of the green power grid supply chain, allocation optimization involves multiple objectives (such as minimizing transportation costs, inventory costs, and carbon emission costs), with complex trade-offs between these objectives. Through steps like population initialization, crossover, mutation, and selection, GA can identify multiple near-optimal solutions within the global search space, providing flexibility for supply chain allocation plans. Additionally, GA's strong robustness makes it suitable for optimization problems with complex constraints (such as timeliness and environmental protection indicators).

Specifically, particle swarm optimization (PSO) is a swarm intelligence optimization algorithm excelling in handling continuous variable optimization problems. Given the continuous nature of transportation path optimization in the power grid supply chain, PSO efficiently optimizes transportation costs and time through collaborative searching of individual particles. Furthermore, the dynamic adjustment mechanism of PSO's inertia weight effectively addresses premature convergence issues, allowing it to find better solutions in complex scenarios. The global search capability of PSO is combined with the local optimization ability of GA, further improving the quality of the allocation optimization plan. In order to enhance its exploration ability, a dynamic inertia weight is introduced, as shown in Equation (11):

$$\omega = \omega_{max} - (\omega_{max} - \omega_{min}) \cdot \frac{g}{g_{max}} \quad (11)$$

ω is the inertia weight. ω_{max} and ω_{min} are the maximum and minimum weight values, respectively.

GA and PSO are integrated into a hybrid optimization algorithm. In the initial stage, PSO is employed for global search, while GA is activated in the later stage to refine local optimization and improve solution accuracy.

Combined with the demand forecasting model in Section 3.3, the forecasting results are updated in real time, and the allocation scheme is dynamically adjusted. The mechanism is realized by the following steps. Real-time input: The predicted demand $D_{t,i}$ is directly used as the input of the optimized model, and the objective function and constraints are updated. Rolling optimization: The optimization algorithm is periodically re-executed using a sliding window approach to ensure that the scheme remains aligned with the most recent data.

To address the complexity and regional distribution of power grid material allocation, a distributed collaborative optimization algorithm is proposed, enabling parallel computation through the regional decomposition of the power grid. This approach includes regional decomposition, where the national power grid is divided into several sub-regions, with each region independently operating the optimization model; master–slave collaboration, in which the master node coordinates data exchange and resource sharing among the sub-regions to maintain the integrity of the global solution; and parallel computing, which leverages the MapReduce framework [21] to efficiently solve large-scale allocation problems within a distributed computing environment. Table 2 displays the algorithm flow.

Table 2. Execution process and function description of the distributed collaborative optimization algorithm.

Step	Explanation
1	The master node initializes global parameters and distributes them to sub-nodes in each region.
2	Each child node independently runs the improved meta-heuristic algorithm and outputs the optimized scheme in the region.
3	The master node summarizes the sub-regional schemes and calculates the global coordination and optimization.
4	According to the real-time data, the regional parameters are dynamically updated, and tasks are redistributed.

4. Analysis of Demand Forecasting and Allocation Optimization Results of Green Power Grid Supply Chain

4.1. Analysis of Demand Forecasting Results

In order to comprehensively evaluate the performance of the demand forecasting model, the following five indicators are selected: MSE, root mean squared error (RMSE), mean absolute percentage error (MAPE), determining coefficient (R^2), and forecasting SI.

The proposed weighted stacking method is compared with other classical prediction models, including LSTM, XGBoost, RF, and support vector regression (SVR). Figure 2 displays the comparison of the prediction performance of different models:

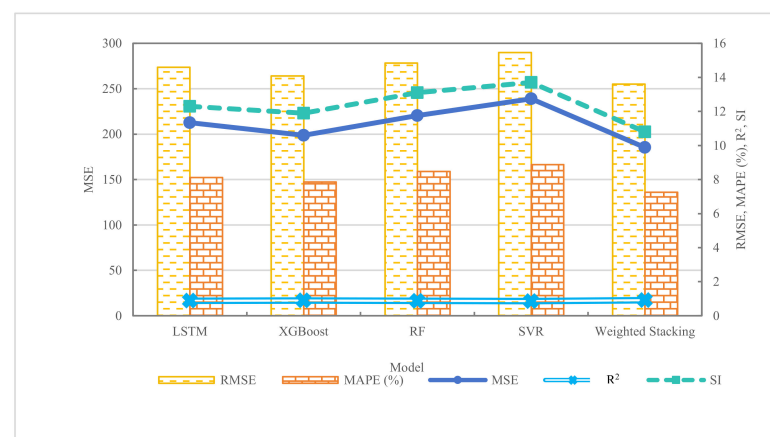


Figure 2. Comparison of the performance of multi-model ensemble methods and other classical prediction models.

As shown in Figure 2, the proposed weighted stacking method outperforms all other models across all indicators of accuracy. With an MSE of 185.3, it is significantly superior, being 13% lower than LSTM and 22% lower than SVR. Additionally, the weighted stacking method exhibits the smallest SI, indicating that its prediction results are less sensitive to variations across different datasets, demonstrating high stability.

Table 3 provides a statistical analysis of the key variables in the historical data. It showcases the statistical characteristics of each variable from multiple perspectives, including mean, standard deviation, distribution characteristics, and key observation points.

Table 3. Descriptive statistical analysis of key variables in historical data.

Variable	Mean	Standard Deviation	Distribution	Key Observations
Historical Demand	500	50	Normal	A strong predictor of demand
Temperature Variation	15	10	Uniform	Significant during extreme conditions
Seasonality	Higher in summer and winter	-	-	Seasonal peaks
Equipment Lifespan	5.2	1.3	Normal	Influences long-term planning
Regional Load	50–80%	-	Left-skewed	Varies significantly by region

Based on Table 3, the historical demand follows a normal distribution, with a mean of 500 and a standard deviation of 50. It is a core variable in demand forecasting and strongly influences the accuracy of the prediction results. The temperature range varies from -10°C to 40°C , significantly affecting seasonal fluctuations in demand and extreme weather conditions, with particularly noticeable demand changes under extreme conditions. The seasonal demand is significantly higher in summer and winter compared to spring and autumn, providing clear time-series dependency information for the forecasting model. The average service life of equipment is 5.2 years, with a standard deviation of 1.3 years. This factor impacts long-term demand planning and should not be overlooked in long-term forecasting. The regional load level shows a left-skewed distribution, with most loads concentrated between 50 and 80%. This reflects the load variability across different regional grids, and offers a basis for regional optimization.

Through feature importance analysis, the contribution of key factors to the demand forecasting model is evaluated. Based on the feature weights of the XGBoost model, the five most important influencing factors are screened out, and their sensitivity to prediction results is analyzed. Table 4 displays the results.

Table 4. Analysis results of key influencing factors and their importance weights based on the XGBoost model.

Factor Name	Importance Weight
Historical demand	35.40%
Temperature change	22.80%
Seasonal characteristics	18.90%
Service life of equipment	15.70%
Regional load level	7.20%

Table 4 suggests that historical demand, temperature fluctuations, and seasonal characteristics are the primary drivers of demand forecasting. In contrast, equipment service life and regional load levels serve a supporting role in long-term forecasting and the analysis of regional disparities. By strategically adjusting the weights of these factors, the model can more accurately capture the dynamic changes in power grid material demand.

4.2. Analysis of Allocation Optimization Results

The core goal of allocation optimization is to reduce the total cost, including transportation cost, inventory cost, and environmental protection costs. The traditional solution refers

to the allocation of materials based on existing dispatch strategies. These strategies typically rely on fixed rules, such as allocation methods based on static demand forecasting and simple route planning. By comparing the optimized allocation scheme with the traditional scheme, the saving effect of each cost item is evaluated, as shown in Figure 3:

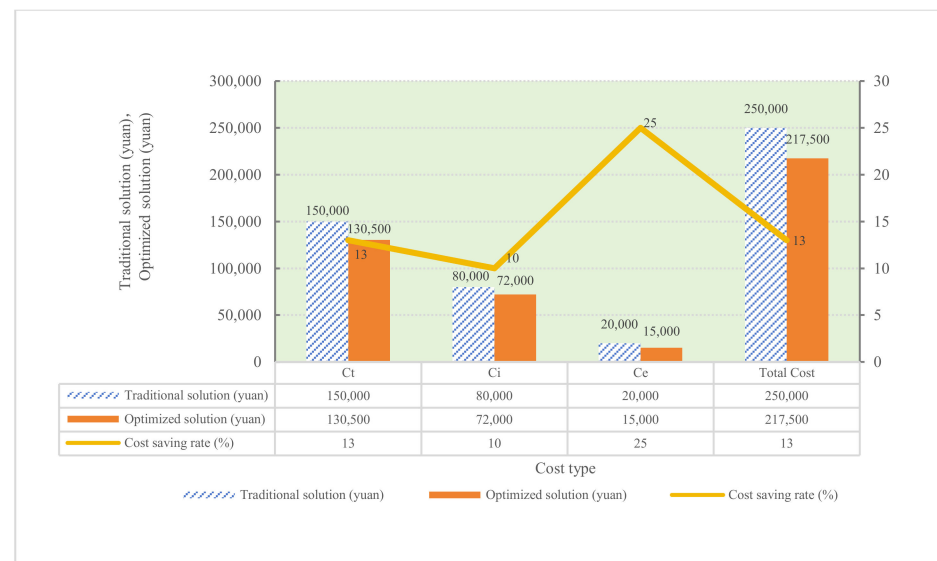


Figure 3. Comparative analysis of the total cost structure between the optimized solution and the traditional solution.

As shown in Figure 3, the optimized scheme achieves a 13% reduction in transportation costs by effectively adjusting transportation routes and modes, thereby minimizing unnecessary mileage. In terms of inventory cost savings, the scheme, guided by demand forecasts and inventory distribution, reduces the storage of surplus and unsellable materials, leading to a 10% decrease in inventory costs. Regarding environmental cost savings, the optimization not only lowers transportation expenses but also reduces carbon emissions during logistics, resulting in a 25% decrease in environmental costs. The absolute difference in environmental protection costs (Ce) is relatively small (reduced from 20,000 yuan to 15,000 yuan, a decrease of only 5000 yuan), but the savings rate is the highest (25%). This is due to the lower base of environmental protection costs in the traditional solution (20,000 yuan). The savings rate is calculated using the equation: $(\text{traditional cost} - \text{optimized cost}) / \text{traditional cost}$. When the base for environmental protection costs is low, even a small absolute difference can result in a higher savings rate. This savings is primarily attributed to the optimized solution's use of low-carbon-emission transportation methods and route planning, which significantly reduces carbon emissions, while reflecting the emphasis of GSCM on environmental protection goals.

Figure 4 illustrates the key changes in the logistics path before and after optimization.

In Figure 4, the optimized scheme reduces the total transportation distance by 20.8% through effective path planning and minimizing redundant routes. The average transportation distance per trip has been cut by 20% through the application of the shortest-path algorithm and optimized demand allocation. Transportation time has decreased by 20%, primarily due to path optimization and the use of a multi-objective scheduling algorithm. The significant reduction in the return empty rate (44.4%) indicates that the optimized scheme more efficiently balances transportation needs across different locations, minimizing resource waste. Additionally, the optimized scheme shortens the single transportation time from 10 h to 8 h, enhancing overall transportation efficiency.

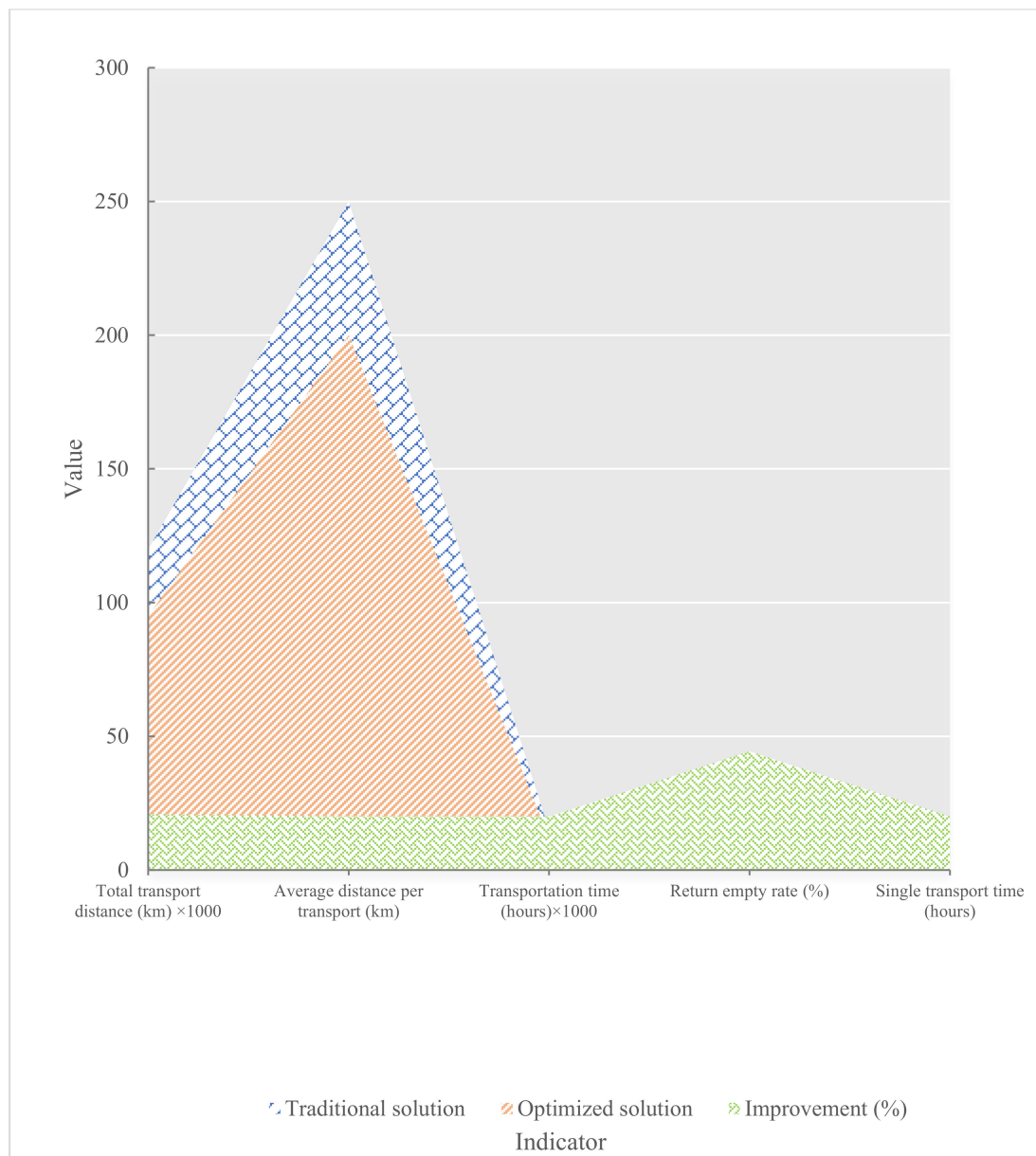


Figure 4. Analysis of key logistics indicators before and after optimization.

In the optimization of the green power grid supply chain, environmental protection costs and carbon emissions are crucial factors. By implementing the optimized allocation scheme, both resource waste and carbon emissions are reduced. Figure 5 displays the environmental impact of the optimized scheme.

In Figure 5, the optimized allocation scheme, which includes rational transportation route and mode planning (such as prioritizing low-carbon vehicles), leads to a 25% reduction in overall transportation carbon emissions. The scheme effectively minimizes unnecessary empty runs and long transportation routes, resulting in a nearly 25% decrease in carbon emissions per trip. In large-scale transportation scenarios, the optimized scheme can reduce carbon emissions by approximately 250 tons, yielding a significant positive impact on the environment.

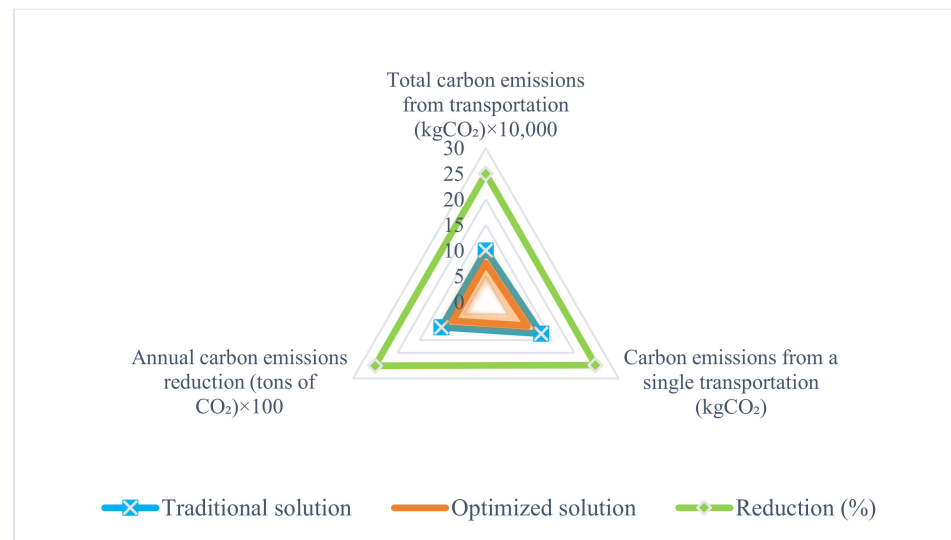


Figure 5. A comparative analysis of overall carbon emissions, carbon emissions from single transportation, and annual carbon reduction before and after optimization.

To further quantify the solution quality of the heuristic algorithm, this paper introduces the Optimality Gap as an evaluation metric. The equation is defined as follows:

$$\text{Optimality Gap} = \frac{\text{Heuristic Solution} - \text{LP Solution}}{\text{LP Solution}} \times 100\% \quad (12)$$

Heuristic Solution: the objective function value obtained by the heuristic algorithm.

LP Solution: the objective function value obtained by LP (theoretical optimal solution).

This paper conducts comparative experiments on the allocation optimization model to evaluate the performance of the improved heuristic algorithm (combining GA and PSO). Table 5 displays the results.

Table 5. Performance comparison of improved heuristic algorithm and LP.

Scenario Number	Scenario Description	Method	Total Cost (Unit: Ten Thousand Yuan)	Optimality Gap (%)	Solution Time (Seconds)
1	Single-region allocation, moderate demand, normal constraints	Improved Heuristic Algorithm	24.5	3.4	12.6
		LP	23.7	-	25.8
2	Cross-region allocation, high demand, urgent timeline	Improved Heuristic Algorithm	32.8	4.1	15.2
		LP	31.5	-	30.5
3	Multi-region allocation, high demand, strict environmental requirements	Improved Heuristic Algorithm	41.2	4.8	18.3
		LP	39.3	-	35.7
4	Single-region allocation, low demand, normal constraints	Improved Heuristic Algorithm	19.6	3.1	11.4
		LP	19	-	24.6

The experimental results in Table 5 indicate that although the solutions obtained by the heuristic algorithm may not be globally optimal, the Optimality Gap is consistently kept within 3–5%. Meanwhile, the solution time of the heuristic algorithm is significantly lower than that of the LP method, making it more practically valuable in large-scale scenarios.

4.3. Method Comparison and Practical Evaluation

This paper compares the application effectiveness of the proposed optimization method with that of traditional methods in the power grid material supply chain and evaluates its potential in practical applications. To comprehensively assess the effectiveness of the “dual-track parallel + dynamic feedback” optimization method proposed, comparative experiments are conducted with traditional methods. In comparison to traditional forecasting methods, demand forecasting is performed using LSTM and RF methods. In the comparison of traditional allocation methods, LP is used to provide the theoretical

optimal solution as a benchmark for reference. The comparison experiments use the same power grid material supply chain dataset to evaluate the performance of different methods in terms of total cost, transportation efficiency, forecasting accuracy, and environmental impact. Figure 6 shows the experimental results.

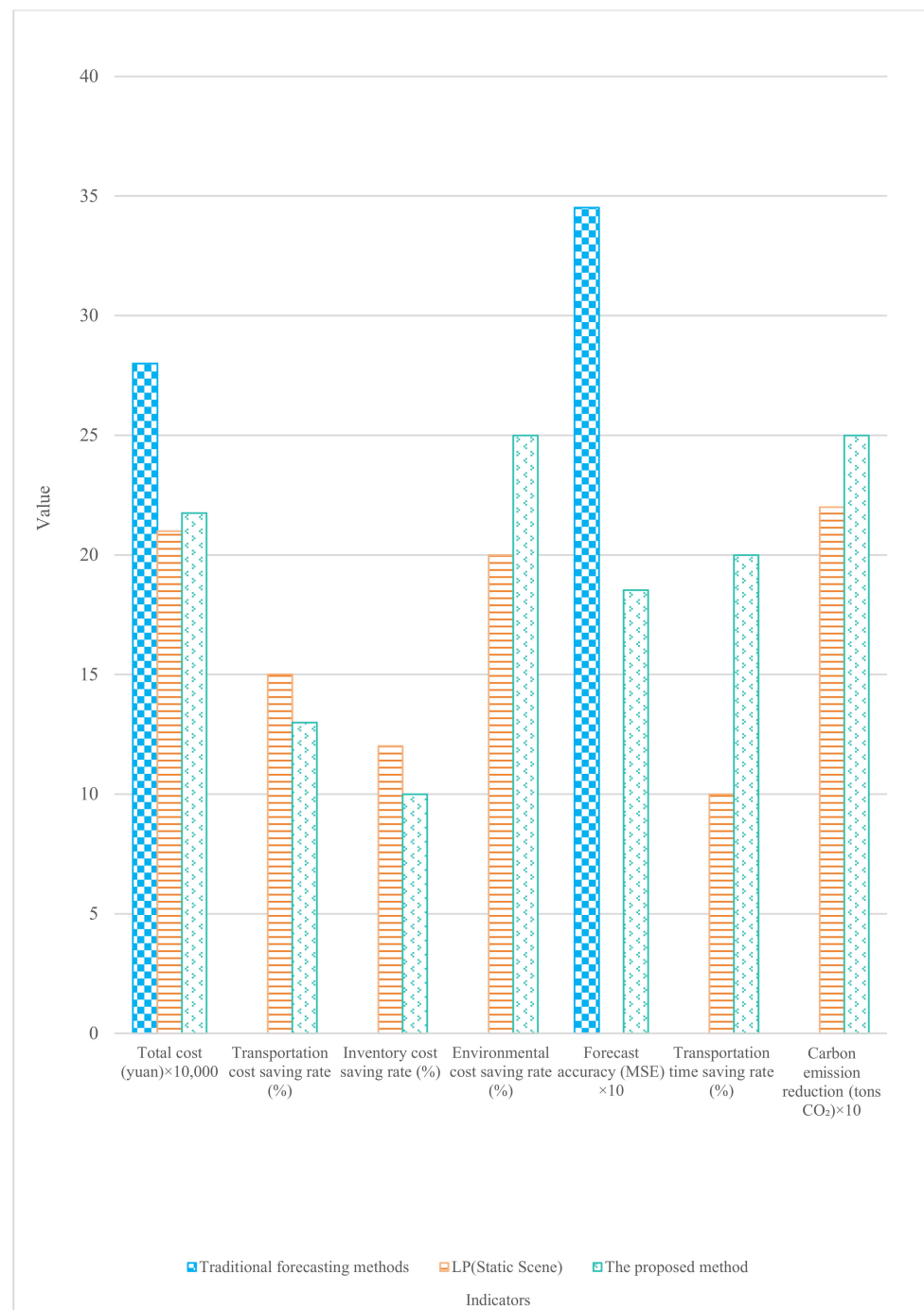


Figure 6. A comparative analysis of the performance of different optimization methods in terms of cost-saving prediction accuracy and environmental benefits.

Figure 6 shows that in a static scenario, the LP method achieves a theoretically global optimal solution with a total cost of 210,000 yuan, significantly lower than the 280,000 yuan of the traditional forecasting method and the 217,500 yuan of the proposed method. However, the LP method is only suitable for static demand scenarios and lacks adaptability to dynamic changes in demand. Furthermore, the LP method performs well in saving

transportation costs, inventory costs, and environmental costs, with savings rates of 15%, 12%, and 20%, respectively. However, it still falls short compared to the proposed method, which achieves a 25% reduction in environmental costs and a decrease of 250 tons in carbon emissions in dynamic scenarios. In terms of forecasting accuracy, the LP method, lacking prediction functionality (MSE shows as 0), does not adapt to dynamic scenarios. The proposed “dual-track parallel + dynamic feedback” method significantly outperforms traditional forecasting methods with an MSE of 185.3, compared to 345.2 for the traditional method. This highlights its strong adaptability in dynamic scenarios. In summary, while the LP method has a clear cost advantage in static scenarios, the proposed method better adapts to the complex and changing demand environment of real-world power grid supply chains through the dynamic feedback mechanism. It is particularly excellent in transportation time savings (20%) and carbon emission reduction (250 tons), demonstrating its practical application value in dynamic optimization.

5. Discussion

First, the performance of the demand forecasting module in addressing complex and dynamic scenarios highlights its advantages. The multi-model fusion strategy significantly enhances the flexibility and stability of the forecasting model by combining the long-term memory capabilities of LSTM, feature importance analysis of XGBoost, and nonlinear fitting ability of RF. This combination not only improves prediction accuracy but also enables the model to adapt to the diversity of demand in the power grid supply chain. However, the model may experience certain delays or prediction errors when handling sudden changes in demand or extreme weather events. For instance, large-scale extreme weather events (such as typhoons or snowstorms) that occur in a short period may lead to insufficient response speed from the demand forecasting model. To address this, further exploration of real-time data augmentation techniques or the introduction of reinforcement-learning-based dynamic adjustment methods could enhance the model’s adaptability during sudden events. Next, in terms of allocation optimization, the distributed collaborative optimization algorithm effectively integrates the advantages of metaheuristic algorithms, and achieves comprehensive optimization of transportation, inventory, and environmental protection costs. Compared to traditional optimization methods, such as LP, the improved GA and PSO overcome the problem of local optima by dynamically adjusting weights and mutation rates, thereby enhancing their solution capabilities in multi-objective scenarios. However, the solution quality of these heuristic algorithms is still influenced by initial parameters and search strategies, which may result in not always achieving the theoretically optimal solution. This paper introduces the Optimality Gap indicator to quantify the difference between heuristic algorithm solutions and theoretical optimal solutions. This improvement provides greater transparency in interpreting the results, but future research should further optimize the adaptive adjustment mechanism for algorithm parameters to narrow the Optimality Gap and improve the algorithm’s generalizability. In terms of environmental impact, the optimized scheme stands out in reducing carbon emissions and saving environmental costs. By reasonably planning transportation routes, reducing empty load rates, and selecting low-carbon-emission transportation vehicles, the optimized scheme aligns closely with the goals of a green supply chain. However, the current environmental impact analysis mainly focuses on carbon emissions as a single indicator. Future work could incorporate additional measurable environmental indicators, such as water resource consumption and energy usage efficiency, to provide a more comprehensive environmental benefit evaluation. Additionally, the cost–benefit analysis of the optimized scheme warrants further exploration, such as comparing the trade-offs between unit transportation costs and environmental benefits before and after optimization, to clearly define the combined contribution of green supply chain optimization to both economic and environmental goals.

6. Conclusions

This paper focuses on the demand forecasting and allocation optimization issues in the green power grid supply chain. It proposes an innovative framework that combines the ML multi-model fusion demand forecasting method with metaheuristic algorithm-based allocation optimization methods. The “dual-track parallel + dynamic feedback” structure achieves deep coupling between demand forecasting and allocation optimization, improving the operational efficiency and environmental benefits of the power grid material supply chain. The research results show that the multi-model fusion strategy significantly improves the accuracy of demand forecasting, while the “distributed collaborative optimization algorithm” dynamically adjusts material allocation schemes, effectively reducing transportation, inventory, and environmental protection costs. It provides a reliable basis for the sustainable management of the green power grid supply chain. Although significant progress has been made, some limitations remain. In terms of model application, while the algorithm performs excellently in medium- and small-scale power grid supply chain scenarios, there is still room for improvement in computational efficiency and real-time responsiveness in large-scale systems. Moreover, the model assumes ideal conditions and does not fully account for complex factors such as sudden demand fluctuations or extreme weather events in real-world applications. Future research should further enhance the model’s robustness and explore technologies like multi-agent collaborative optimization and real-time data update mechanisms to improve its ability to handle complex scenarios. To promote the practical application of the research results, this paper proposes the following implementation strategies. Deployment testing in real power grid systems: the model’s stability and adaptability in power grid material supply chains of different regions and scales are gradually verified, and algorithm parameters are optimized based on real-time feedback. Introduction of carbon footprint assessment and green energy scheduling: the environmental impact analysis framework of the model is expanded to include more environmental indicators such as carbon emission intensity, energy efficiency, and resource utilization, enhancing its applicability in green development. Optimization of computational efficiency and real-time processing capability: for large-scale supply chain scenarios, solutions based on cloud computing and distributed computing architectures are explored to support real-time forecasting and allocation optimization needs. The practical significance of this paper lies in providing an accurate prediction and optimization tool for green power grid material supply chain management. It also offers innovative solutions for reducing transportation costs, minimizing resource waste, optimizing logistics paths, and cutting carbon emissions. These results provide important theoretical support and practical guidance for green power grid construction and offer a replicable model for green supply chain optimization in other industries. In the future, as the concept of green development continues to deepen, the methods proposed are expected to be applied in a broader range of scenarios, contributing to the achievement of global sustainable development goals.

Author Contributions: X.S.: writing—review and editing, conceptualization, methodology, resources; H.R.: writing—review and editing, conceptualization, data curation, project administration; J.L.: writing—original draft, formal analysis, visualization, validation. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China as part of “A Study on Social Capital, CEO Power, Corporate Resource Allocation & Its Economic Consequences”, grant number 20CGL011, and the Ministry of Education Industry–Academia Cooperation and Collaborative Talent Cultivation Project, grant number 231101339153047.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

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