

Research on Green Performance Evaluation of Distribution Network Material Suppliers Considering Carbon Footprint

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Abstract. The green performance evaluation of distribution network material suppliers considering carbon footprint is crucial for promoting low-carbon development in power grids. This paper constructs a comprehensive evaluation system from economic, technical, and green dimensions, defines a carbon footprint accounting method for suppliers, and proposes an improved AHP-SVR evaluation model. Validated on a provincial power box project, the AHP-SVR model achieves a prediction error within $\pm 4.2\%$, significantly outperforming the traditional AHP method ($\pm 8.7\%$). It also demonstrates superior performance across key metrics—MAE, RMSE, R^2 and Deviation Rate. The model effectively distinguishes suppliers' green performance and provides reliable decision support for distributor supplier selection.

Keywords: Distribution network material suppliers; Green performance; Carbon Footprint; AHP-SVR.

1. Introduction

Under the "double carbon" goal, distribution network material procurement needs to pay more attention to low carbon, scientific evaluation of supplier green performance has become the key to green supply chain management of power grid enterprises. Existing research generally ignores environmental factors such as carbon footprint, and lacks systematic and quantitative green evaluation system. It is urgent to build a scientific and comprehensive evaluation model to support supplier selection and incentive.

In the field of power grid material supplier evaluation, existing studies have established multi-criteria systems incorporating environmental indicators [1-3], with evaluation methods such as entropy-weighted TOPSIS, BP neural networks, DEA, and SFA being applied [4-7]. Carbon footprint quantification has been conducted for specific equipment like cables and transformers using LCA and ISO standards [8-9]. However, under carbon constraints, research on deeply integrating carbon footprint into green performance evaluation remains notably insufficient, particularly lacking comprehensive evaluation models capable of handling small-sample data and nonlinear relationships.

Based on the demand of distribution network green supply chain construction, this paper constructs a comprehensive evaluation index system of supplier green performance considering carbon footprint, proposes a distribution network material supplier green performance evaluation model based on improved AHP-SVR, optimizes AHP weight determination process by SVR, enhances objectivity and consistency of weight, and provides theoretical basis and decision support for low carbon management of power grid enterprise suppliers.

2. Construction of an Evaluation Index System

Under the low-carbon development background, the selection of distribution network suppliers requires a balanced consideration of both economic-technological capabilities and green low-carbon

performance. This paper constructs a comprehensive evaluation system from three dimensions—economic, technological, and green—comprising 9 first-level indicators and 25 second-level indicators, to systematically assess suppliers' green performance.

Table 1 Evaluation Indicator System for Distribution Network Material Suppliers

Primary Indicators	Specific indicator	Secondary Indicators
Economic Benefits A	Procurement CostA1	Product unit priceA11
		Logistics transportation costsA12
		Transaction CostsA13
	Product Life Cycle Cost (LCC)A2	Operational Energy Consumption CostA21
		Upkeep and Overhaul CostsA22
		Residual Value and Disposal CostA23
	financial stabilityA3	Enterprise asset-liability ratioA31
		Net profit growth rateA32
		Order performance bondA33
Technical Performance B	Product qualityB1	Ex-factory qualification rate of productsB11
		First pass rate of acceptance sampling inspectionB12
		Completeness of quality certification system (such as ISO9001)B13
	technical capacityB2	Qualification of technical team and proportion of R investmentB21
		Number of patents (especially green technology patents)B22
		New product/new process development capabilityB23
	Performance and ServicesB3	on-time delivery rate B31
		Timely rate of after-sales fault handling and spare parts supply abilityB32
Green Properties Performance C	carbon emissionC1	Carbon footprint per unit product (CO ₂ e/unit·km·ton)C11
		Rate of reduction in total carbon emissionsC12
		Green electricity usage ratioC13
	Resource consumptionC2	Comprehensive energy consumption per unit product (tons of standard coal/unit product)C21
		Raw material utilization/waste recoveryC22
	Environmental management and complianceC3	Certification of environmental management system (such as ISO14001)C31
		Proportion of renewable materials usedC32
		Green product certification (such as environmental labeling products, energy-saving certification)C33

3. An Optimized Evaluation Model Based on AHP-SVR

3.1 Quantitative Calculation of Carbon Footprint

According to the System of Greenhouse Gas Accounting (GHG Protocol), greenhouse gas emission sources can be divided into three categories: Scope 1 (direct emissions), Scope 2 (indirect emissions from electricity) and Scope 3 (indirect emissions from value chain). This study quantifies Scope 1 and 2 using supplier energy consumption data and emission factors, while Scope 3 is estimated via key raw material procurement volumes (e.g., copper, steel). Calculation follows the latest Provincial Greenhouse Gas Inventory Guidelines.

For each emission source, the basic formula is (1), Calculate total carbon footprint using (2), Calculation of carbon footprint per unit product (core evaluation indicator) using (3).

$$E_i = AD_i * EF_i \quad (1)$$

$$\text{Total Carbon Footprint}(\text{CO}_2\text{e}) = \sum E_{\text{scope1}} + \sum E_{\text{scope2}} + \sum E_{\text{scope3}} \quad (2)$$

$$\text{Unit Product Carbon Footprint}(\text{CO}_2\text{e/unit}) = \frac{\text{Total Carbon Footprint}(\text{CO}_2\text{e})}{\text{Reporting Period Product Output(units)}} \quad (3)$$

Where: E_i =CO₂ emissions from this source, AD_i =Activity data (e.g.m³ of natural gas consumed), EF_i =Emission factors corresponding to the activity(eg;kg CO₂e/m³),product output (units) refers to the total quantity of similar distribution network materials produced within the accounting period(usually one year)(e.g.100 distribution transformers)

3.2 The AHP-SVR Method

The AHP-SVR model takes the indicator weights derived from traditional AHP (expert scoring) as initial parameters for SVR, with supplier indicator data as input and known supplier scores (post-event evaluation) as the learning objective. By minimizing errors to adaptively optimize weight parameters, it ultimately constructs a data-driven model capable of directly outputting objective evaluation results.The steps are as follows:

An improved AHP scale, $\ln(9e/9)-\ln(17e/1)$, was used,where experts were invited to rate the influencing factors.A hierarchy structure and a judgment matrix are created.

Calculating weights by adopting a root method and then raising the judgment matrix to the nth power using(4);After normalization, weight coefficient w_i can be obtained as (5).

$$w_i = \sqrt[n]{\prod_{j=1}^n a_{ij}}, \text{ here } (i, j = 1, 2, \dots, n) \quad (4)$$

$$w_i = \frac{w_i}{\sum_{i=1}^n w_i} \quad (5)$$

Using MATLAB to calculate the maximum eigenvalue $\lambda_{\max}$ of the judgmentmatrix,applying the test formula (6) to calculate the consistency index CI, formula (7) to calculate the random consistency ratio CR.RI is the average random consistency index. When $CR < 0.10$, the judgment matrix has satisfactory consistency, otherwise, the judgment matrix is adjusted.

$$CI = (\lambda_{\max} - n) / (n - 1) \quad (6)$$

$$CR = CI / RI \quad (7)$$

Let the sample set be: $\{(x_1, y_1), \dots, (x_l, y_l)\} \in (x^* y)$, here $i = 1, 2, \dots, l$, and $x_i \in x \subset R^n$ for which the input vector is the output vector and l is the number of samples. Linear regression is performed using (8).

$$f(x) = \langle W \cdot X \rangle + b \quad (8)$$

Where: $W = (w_1, w_2, \dots, w_n)$ weight vector, b is the threshold. The equation is expressed as an optimization problem(9), Applying Lagrange multiplier method to solve this problem, it can be transformed into the following dual problem(10).

$$\begin{cases} \max_{\alpha, \alpha^*} \left\{ L = -\frac{1}{2} \sum_{i=1}^l \sum_{j=1}^l (\alpha_i - \alpha_j^*) (\alpha_j - \alpha_i^*) K(x_i, x_j) - \varepsilon \sum_{i=1}^l (\alpha_i - \alpha_i^*) + \sum_{i=1}^l y_i (\alpha_i - \alpha_i^*) \right\} \\ \sum_{i=1}^l \alpha_i = \sum_{i=1}^l \alpha_i^* \\ 0 \leq \alpha_i \leq C, 0 \leq \alpha_i^* \leq C \end{cases} \quad (9)$$

$$\begin{cases} \min_{w,b,\xi} \varphi(w) = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^l (\xi_i + \xi_i^*) \\ y_i - \langle w \cdot x \rangle - b \leq \varepsilon + \xi_i \\ \langle w \cdot x \rangle + b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i^* \geq 0, \xi_i \geq 0, i=1,2,\dots,l \end{cases} \quad (10)$$

Where: ξ^*, ξ are relaxed variables, The larger C means the greater the penalty for data points exceeding, parameter C governs the trade-off between model complexity and training errors, while the parameter ε defines the margin of tolerance in the insensitive loss function.

To solve the above problem, we can obtain the regression function of support vector machine as(11)

$$f(X) = \sum_{x_i \in S_v} (\alpha_i - \alpha_i^*) K \langle x_i \cdot x \rangle + b \quad (11)$$

4. Empirical Analysis of the Model

This study utilizes 2020-2025 electrical box supplier data, with actual supplier performance scores as the benchmark, to compare the evaluation effectiveness between traditional AHP and the AHP-SVR model. Results demonstrate that the AHP-SVR model, through data-driven weight optimization, achieves higher alignment with actual performance.

4.1 Data Preprocessing

Missing values were treated by linear interpolation, outliers were identified and corrected by Z-score method. The sample data was randomly divided into a training set and a testing set in a 7:3 ratio, and simulation tests were conducted using MATLAB.

4.2 Forecasting Results and Analysis

Aiming to minimize the deviation between model outputs and expected outcomes, this section employs a Support Vector Regression (SVR) model to identify the internal mapping relationship that most accurately predicts scores through multiple simulation runs. In the figure 1, the red curve represents the Y values obtained from the model training, while the blue curve denotes the expected output. As shown in the graph, the training results align most closely with the expected output when $C=0.05$, $\varepsilon=0.045$, the parameter is determined as follows:

$$C=0.05, \varepsilon=0.045, K \langle x_i \cdot x \rangle = (x_i * x + 15)^2 \quad (12)$$

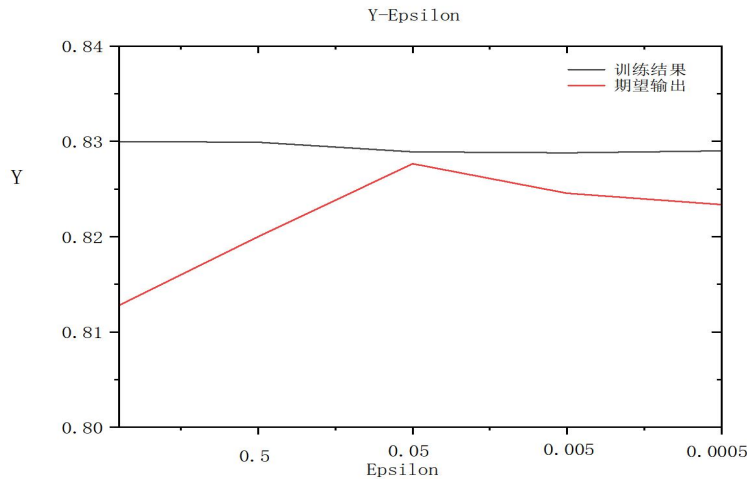


Figure 1. illustrates the influence of adjusting the ε parameter on the output Y

Based on actual supplier performance in operations as the benchmark, Figure 2,3 evaluates the performance of the AHP-SVR model by comparing its predictions with the results from the traditional AHP method. Figure 2 and Figure 3 present the prediction results for the "Three-Phase-1-Stainless Steel-150A-Suspended" specification using the traditional AHP and AHP-SVR methods, respectively.

As shown in the figures 2 and Figure3, The evaluation curve of the traditional AHP method shows a significant deviation from the actual value curve, indicating poor goodness of fit. In contrast, the prediction curve of the AHP-SVR model almost overlaps with the actual value curve, with errors effectively controlled within a narrow range. This not only confirms that the AHP-SVR model significantly improves prediction accuracy but also demonstrates its potential for practical decision-making support.

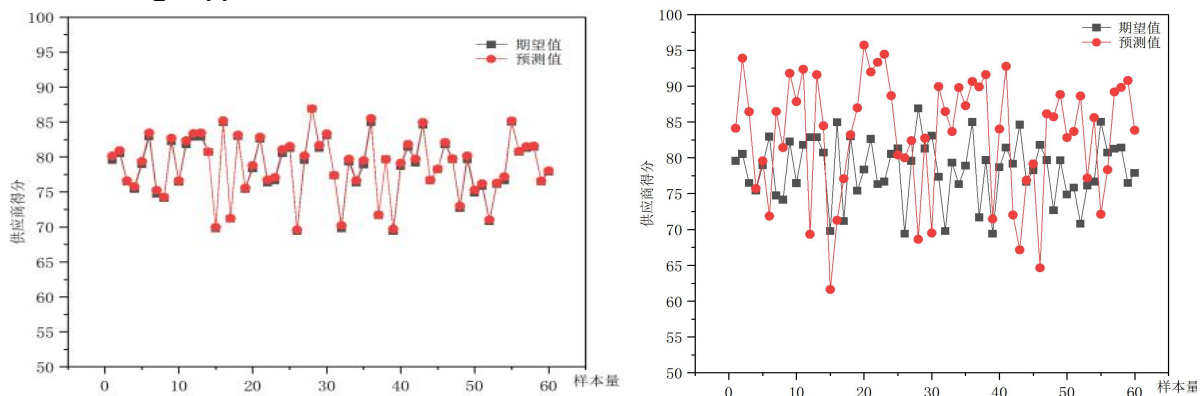


Figure2, Figure 3 present the supplier evaluation prediction results for the "Three-Phase-1-Stainless Steel-150A-Suspended" using AHP-SVR and traditional AHP methods.

To further validate the effectiveness of the AHP-SVR model, this study performed a quantitative error analysis, examining both the absolute deviation and the consistency in trend variation between the predicted and actual supplier performance values. From table 2, The evaluation scores of the traditional AHP method show significant deviations from actual performance values, whereas the AHP-SVR model demonstrates substantially improved accuracy in assessing electricity meter box suppliers. Empirical results indicate that the average deviation between the predicted scores of the AHP-SVR model and actual performance scores is controlled within $\pm 4.2\%$, achieving a precision improvement of over 50% compared to the $\pm 8.7\%$ deviation of the traditional AHP method, thereby validating the superiority of the data-driven approach in supplier evaluation.

Table 2 Comparison Between Forecasting AHP and AHP-SVR

Model	Metric Supply	MAE	RMSE	R ²	Deviation Rate
AHP-SVR	Three-Phase-1-StainlessSteel-150A-Suspended	0.000103	0.000256	0.907	3.73%
	Single-Phase-12-PC+ABS-60A-Suspended	0.000109	0.000125	0.915	-4.00%
	Single-Phase-9-PC+ABS-Steel-60A-Floor-Mounted	0.000211	0.000206	0.935	3.81%
	Single-Phase-9-StainlessSteel-60A-Floor-Mounted	0.000113	0.000227	0.912	-4.18%
	Three-Phase-2-Stainless Steel-100A-Floor-Mounted	0.000208	0.000206	0.904	-1.70%
AHP	Three-Phase-1-Stainless Steel-150A-Suspended	0.000247	0.000325	0.731	7.73%
	Single-Phase-12-PC+ABS-60A-Suspended	0.000218	0.000211	0.634	-8.77%
	Single-Phase-9-PC+ABS Steel-60A-Floor-Mounted	0.000308	0.000214	0.491	-7.81%
	Single-Phase-9-Stainless Steel-60A-Floor-Mounted	0.000225	0.000245	0.804	-8.18%
	Three-Phase-2-Stainless Steel-100A-Floor-Mounted	0.000280	0.000214	0.623	-6.70%

5. Conclusions

This study focuses on the green performance evaluation of distribution network material suppliers and has achieved the following results: A comprehensive evaluation system integrating carbon footprint was established, with quantification methods covering Scope 1 to 3 based on the GHG Protocol; an innovative AHP-SVR model was proposed, which optimizes weights through data-driven mechanisms, effectively overcoming the subjective bias of traditional AHP. Empirical results show that the prediction deviation of the AHP-SVR model is controlled within $\pm 4.2\%$, representing an improvement of over 50% compared to the $\pm 8.7\%$ deviation of traditional AHP. This method provides a decision-making tool combining subjective and objective advantages for low-carbon supplier management in power grid enterprises, demonstrating significant theoretical value and application prospects.

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