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CARBON FOOTPRINT TRACEABILITY AND RESPONSIBILITY ALLOCATION IN GREEN SUPPLY CHAINS WITH PRODUCT LIFECYCLE MANAGEMENT

Abstract: This study proposes a framework for tracing carbon footprints and allocating emission reduction responsibilities in green supply chains by integrating Product Lifecycle Management (PLM) with a Discrete Hopfield Neural Network-based Analytic Hierarchy Process (DHNN-AHP). By constructing an integrated "trace-evaluate-allocate" model, it achieves systematic tracking of carbon footprints across the entire chain of raw material acquisition, production, distribution, usage, and recycling, while introducing DHNN-AHP for dynamic low-carbon performance evaluation of suppliers. Based on this, a responsibility allocation mechanism is proposed, grounded in carbon contributions and performance results, to promote overall carbon efficiency coordination in the supply chain. A case study using cathode material suppliers as an example demonstrates that this method enhances the accuracy of supply chain carbon management while balancing environmental and economic benefits, providing methodological support for the governance and policy coordination of green supply chains under carbon neutrality goals.

Keywords: carbon footprint traceability, product life cycle management, green supply chain, Discrete Hopfield Neural Network (DHNN), responsibility sharing, carbon emission reduction

Introduction

The implementation of carbon border adjustments and mandatory carbon footprint disclosure has intensified the need for precise supply chain carbon management [1]. Currently, the international community limits the carbon footprint of enterprises by implementing carbon emission regulations, and the rising environmental awareness of consumers also prompts the market to increasingly favour low-carbon products [2]. Against the backdrop of accelerated global carbon regulation, the EU's Carbon Border Adjustment Mechanism (CBAM) has entered a transition period in 2023 and is scheduled to be fully implemented in 2026. China is promoting the establishment of a national carbon footprint management system through its „dual carbon" goals and related technical standards. ESG [3, 4] disclosure mandates further reinforce the need for supply-chain carbon management. In this context, how to scientifically trace the carbon footprint of products and reasonably share the responsibility of emission reduction has become a key challenge for the low-carbon [5, 6] transformation of supply chain.

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Against the backdrop of the accelerated green transformation of global supply chains, establishing an accurate carbon footprint tracking system and a scientific mechanism for allocating emission reduction responsibilities has become a core foundation for driving overall emission reductions across the industrial chain. Clear allocation of emission reduction responsibilities can resolve the problem of ambiguous environmental responsibilities within the supply chain, stimulate collaborative efforts among multiple stakeholders, and promote the advancement of carbon management from the level of individual enterprises to the level of whole-chain system optimisation. However, traditional carbon management methods are often limited to a single enterprise or production ring [7, 8], and it is difficult to cope with the complex needs of multi-actor collaboration and cross-link optimisation. Supplier evaluation of low-carbon products is still based on the traditional data collection and uploading system [9, 10], which is time-consuming and prone to disputes, making it difficult to form a precise, traceable, fair and efficient green supply chain [11] and provide systematic solutions [12]. Researchers in China have developed an intelligent green supplier risk assessment system that combines Natural Language Processing (NLP) and Life Cycle Assessment (LCA) [13], the green supplier evaluation method based on rough set-gray correlation TOPSIS has been proposed for high-energy consuming enterprises, the intelligent evaluation of low-carbon suppliers has been shifted from single indicator screening to multi-source data fusion decision-making system, and the use of neural network algorithms or hybrid models fused with the traditional supply chain [14], which can improve the logistics distribution [15, 16], site selection [17], supply chain management [18, 19] and other issues, in which supply chain management not only involves risk management [20-22], but also includes the green supply chain, blockchain application [23], e-commerce [24], workshop production and other aspects of the detailed study [25, 26], the industry supply chain carbon emissions are inseparable from the carbon footprint of the product lifecycle management [27], the traceability of the carbon footprint reflects the historical traceability of environmental responsibility, and the responsibility ratio proposed in this paper will indicate the future direction of emission reduction responsibilities.

Traditional decision-making methods have established a solid foundation in the field of green supplier evaluation, with the Analytic Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) being particularly widely applied. AHP effectively integrates expert experience by constructing hierarchical structures and judgment matrices [28], enabling the quantification of qualitative issues. However, the determination of weights in AHP is highly subjective, and once established, these weights remain static throughout the decision-making process, failing to capture the real-time dynamics and uncertainties inherent in supplier performance [29]. TOPSIS ranks alternatives based on their distances from positive and negative ideal solutions, offering conceptual clarity. Nevertheless, its outcomes are heavily influenced by initial weight assignments and distance metrics, and it lacks built-in mechanisms to handle data noise or support adaptive weight updating [30, 31]. Although hybrid approaches - such as integrating rough sets, grey relational analysis, or combining AHP with TOPSIS - have been proposed to incorporate both subjective and objective weighting [32], these models still operate under a framework of “static weighting & linear ranking”.

This study proposes a Discrete Hopfield Neural Network-based Analytic Hierarchy Process, DHNN-AHP integrated framework within Product Lifecycle Management, PLM-based carbon traceability systems to dynamically allocate emission responsibilities across multi-tier suppliers.

Conceptual framework: traceability-assessment-apportionment

Product Carbon Footprint (PCF) refers to the quantitative index of the total greenhouse gas emissions during the whole life cycle [33] of a product. For carbon footprint accounting, the Input-Output Life Cycle Assessment (IO-LCA) model is widely used for industry-level analysis. The study shows that indirect carbon emissions are significantly higher than direct emissions in China's industry supply chains, with the sixth tier of indirect carbon emissions (i.e., the upstream-most activity of the supply chain) accounting for the largest share, especially in the power and heat production and oil processing sectors. This highlights the need for cross-tier collaboration to reduce emissions.

According to Yang and Ji [34] and other studies, supply chains can be categorised into three types based on carbon footprint characteristics: high manufacturing carbon footprint type (e.g., iron and steel, chemical industry), high distribution carbon footprint type (e.g., fresh food [35], logistic services), and high usage carbon footprint type (e.g., automobiles [36, 37], home appliances). PCF covers five stages: raw material acquisition, manufacturing, logistics and transportation, product use and end-of-life recycling. We have determined the approximate intervals of carbon emission characteristics for each stage of the life cycle as shown in Figure 1.

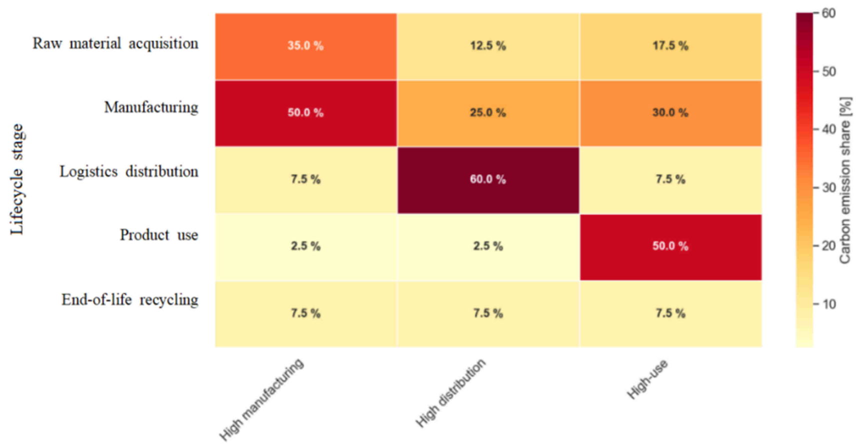

Fig. 1. Comparison of carbon footprint characteristics of product life cycle stages

Aiming at the difficulty of intelligent evaluation of low-carbon suppliers, this paper constructs a three-in-one model of "Traceability-Evaluation-Apportionment", which mainly includes carbon footprint data collection, DHNN-AHP supplier evaluation and the design of a dynamic apportionment mechanism of emission reduction responsibility based on carbon contribution. Based on this traceability framework, we next introduce a DHNN-AHP evaluation mechanism to quantify suppliers' low-carbon performance dynamically.

Methodology: DHNN-AHP for dynamic evaluation

As stated in the introduction, traditional methods exhibit fundamental limitations including inflexible weight structures, limited resilience to data interference, and an inability to learn from or adapt to new information [38, 39]. In contrast, the proposed DHNN-AHP fusion model introduces a paradigm shift toward an ecological engineering approach that emphasises traceability and dynamic resource allocation [40]. Unlike incremental modifications of conventional techniques, this model embeds AHP's hierarchical transparency into a dynamic neural architecture capable of real-time weight adjustment and noise-resistant optimisation. Compared to feedforward networks that require extensive training, DHNN offers faster convergence better suited to rapid decision-making contexts. Moreover, while deep learning models often act as "black boxes", the proposed framework maintains interpretability through AHP's structure, allowing decision-makers to trace evaluation outcomes back to indicator-level contributions.

Traditional supplier evaluation is often influenced by subjective factors, and Hopfield neural network, as a recursive neural network with associative memory and optimisation solving ability, has significant advantages in solving combinatorial optimisation problems. This paper combines the AHP and DHNN to construct an objective quantitative evaluation model.

Indicator system and Delphi weighting

Construct secondary indicators from the dimension of environmental performance, the carbon efficiency dimension selects two key indicators: absolute intensity (carbon emissions per unit of output value) and relative structure (proportion of clean energy), which can comprehensively measure the energy utilisation efficiency and green structure level of suppliers. The technical dimension of emission reduction comprehensively characterises its long-term commitment and innovation capacity in emission reduction through hardware investment (carbon capture investment) and soft power (degree of process innovation). The green certification dimension objectively reflects the maturity of its environmental management and the market low-carbon recognition of its products through system certification (ISO certification level) and product certification (carbon label level).

This study conducted two rounds of Delphi questionnaire surveys among 15 experts from academia (low-carbon research professors), industry (supply chain managers), and policy (ecological environment department experts). The experts compared the importance of each indicator pairwise and constructed a judgment matrix. We use the geometric mean method to aggregate the judgments of all experts and calculate the weights of each indicator. The average random consistency ratio (CR) of all judgment matrices was lower than 0.1, passing the strict consistency test, indicating that the expert judgment has good consistency. The weights of the first-level and second-level indicators were finally determined, among which „carbon efficiency" had the highest weight (0.6), highlighting that experts believe that direct production energy efficiency is the top priority and most crucial link in current emission reduction. Emission reduction technology" and „green certification", as supporting dimensions, together form a complete system for evaluating the comprehensive low-carbon capabilities of suppliers. The evaluation index system is shown in Table 1.

Table 1

Evaluation index system

First-level indicators	Second-level indicators	Weighting
Carbon efficiency	Unit carbon emission	0.6
	Clean energy ratio	0.4
Emission reduction technology	Carbon capture investment	0.5
	Process innovation	0.5
Green certification	ISO certification level	0.4
	Carbon label level	0.6

We use the Extreme Value method to normalise the data of positive indicators (such as ‘Clean Energy Ratio’, ‘Carbon Capture Investment’ and ‘Process Innovation’) and negative indicators (such as ‘Unit Carbon Emission’). For graded indicators (such as ‘ISO certification level’ and ‘carbon label level’), we first convert them into numerical values (e.g., None = 0, Basic = 1, Advanced = 2; Bronze = 1, Silver = 2, Gold = 3). Subsequently, we standardise these values using the aforementioned extreme value method along with continuous indicators, thereby mapping them to the interval [0; 1] for weighted calculations.

AHP procedure

In this chapter, we construct judgment matrix *A*, calculate the feature vector, and calculate whether the total hierarchical ranking passes the consistency test, i.e., whether it satisfies *CR* (Consistency ratio) < 0.1.

$$A = \begin{bmatrix} 1 & c_{12} & c_{13} \\ \frac{1}{c_{12}} & 1 & c_{23} \\ \frac{1}{c_{13}} & \frac{1}{c_{23}} & 1 \end{bmatrix} \tag{1}$$

where *c* is an element in the judgment matrix, representing the relative importance comparison value between two factors.

Let us calculate ω:

$$\mathrm{A}\omega = \lambda_{max}\omega \tag{2}$$

where λ_{max} is the maximum eigenvalue of matrix A, ω is the feature vector corresponding to λ_{max}, which is the weight vector of each feature after normalisation.

Let us calculate whether the total hierarchical ranking passes the consistency test, i.e., whether it satisfies *CR* < 0.1. To calculate the consistency index, *CI*, we use equation:

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{3}$$

where *n* represents the number of factors being compared in matrix A.

We can determine *CR*:

$$CR = \frac{CI}{RI} \tag{4}$$

where RI: Random consistency index.

DHNN optimisation mechanism

Figure 2 shows the flowchart of DHNN, demonstrating the logical relationship of the algorithm. The detailed steps and specific indicator explanations are as follows.

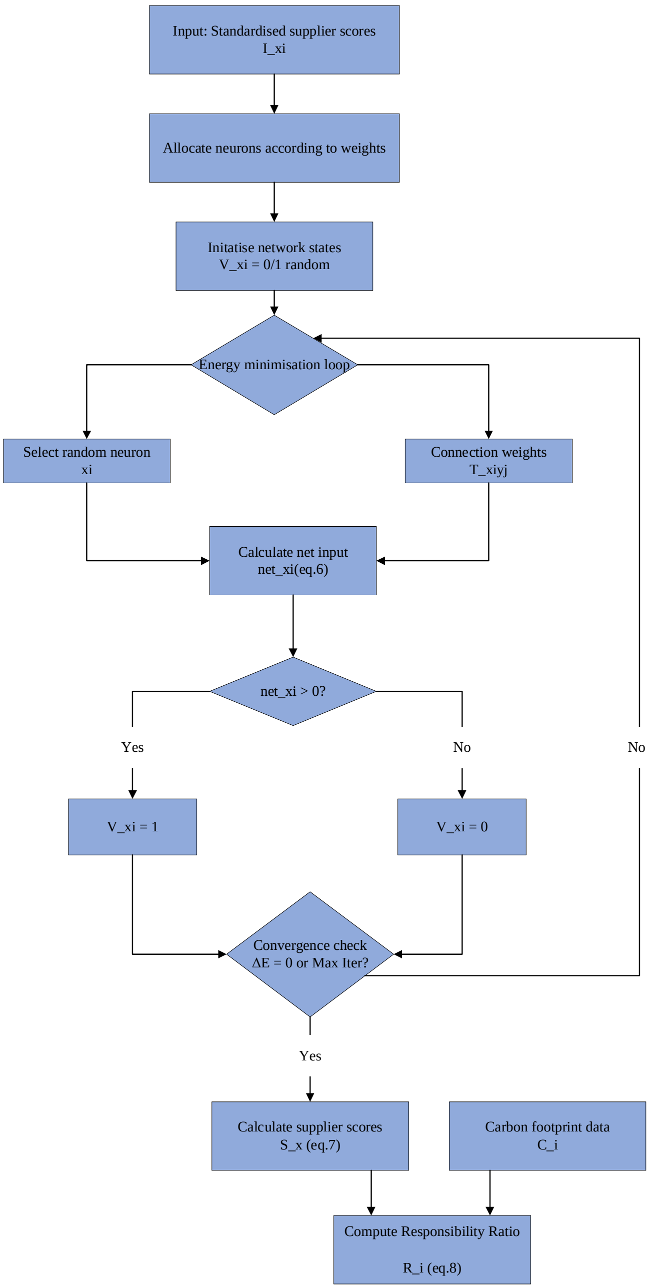

Fig. 2. DHNN flowchart

- *Allocation of neurons according to weights*

Allocate neuron resources according to the proportion of weights, and allocate more neurons for high weight indicators.

- *Energy function, E*

Define the neuron state, i.e., the activation value of supplier x at position i, minimise the energy by asynchronous updating, and output the stable state which is the optimal supplier sorting. Equation (5) represents the network energy function minimised by asynchronous updates:

$$E = -\frac{1}{2}\sum x \sum i \sum y \sum j\, T_{xiyj} V_{xi} V_{yj} - \sum x \sum i\, I_{xi} V_{xi} \tag{5}$$

where I_{xi} is an external input, determined by the supplier's standardised score in this metric; V_{xi} denotes the activation state of supplier x at neuron i, which is 0 or 1; j and V_{yj} are variables that are completely symmetrical to i and V_{xi}, used to traverse and represent the states of all neurons in the network and the connections between them;

T_{xiyj} for the connection weights, when $x \neq y$ & $i = j$, is a negative connection, belonging to the inhibitory activation state, $T = -0.7$, this negative value ensures that the network tends to perform exceptionally well with only one supplier on a specific metric; when $x = y$ & $i \neq j$, it indicates a positive connection, representing a facilitative activation state, with $T = 0.3$, suggesting that the same supplier should develop in coordination across different metrics. This positive value encourages suppliers to balance their performance across various indicators, avoiding severe weaknesses; in other cases for 0. It is determined through Grid Search optimisation on a validation dataset containing 10 sets of known rankings that under this parameter setting, the network's convergence and ranking results are not sensitive to minor changes in parameter values, as long as the relationship $|T\_\text{competition}| > |T\_\text{cooperation}|$ is maintained, the ranking order remains stable. This set of parameters forms a robust combination of 'hyperparameters' that enables the system to operate efficiently and reliably.

- *Asynchronous state update convergence*

Select neurons in random order and calculate the net input, net_{xi}:

$$net_{xi} = \sum_y \sum_j T_{xiyj} V_{yj} + I_{xi} \tag{6}$$

Termination condition: the energy function E no longer changes or the maximum number of iterations is reached.

- *The supplier score, S_x*

To calculate the supplier score, we use equation:

$$S_x = \frac{1}{n_x} \sum\nolimits_{i \in G_x} V_{xi} \tag{7}$$

If $net_{xi} > 0$, then V_{xi} is 1, otherwise 0.
where: G_x - neuron group of supplier x, n_x - the number of neurons in the group.

Dynamic responsibility allocation formula

Establish the dynamic responsibility apportionment model, the formula for responsibility ratio R_i is as follows:

$$R_i = \alpha \cdot \frac{C_i}{\sum C} + \beta \cdot \frac{1/S_i}{\sum(1/S)} \tag{8}$$

where: C_i - carbon footprint contribution value [tonnes of CO_2/month] of supplier i, S_i - DHNN-AHP evaluation score of supplier i, α - industry benchmark coefficient (take 0.7), β - adjustment coefficient (take 0.3).

The setting of this parameter group (0.7, 0.3) is based on a baseline scenario established after extensive literature research and expert consultations, balancing fairness and incentivisation. The model's flexibility allows managers to adjust the values of α and β according to the specific strategic goals of the supply chain (such as focusing more on fairness or more on incentives). Our analysis shows that when α and β vary within a reasonable range (e.g., α from 0.6 to 0.8), the proportion of responsibility for each supplier may change, but their relative ranking remains unchanged, demonstrating the robustness of the allocation results and the management guidance value of the model.

Case demonstration: cathode material supply chain

The evaluation of low-carbon suppliers is a multi-objective combinatorial optimisation problem DHNN can converge to a low-energy state quickly and efficiently through its asynchronous update rules. Applying the DHNN-AHP model to the evaluation of low-carbon suppliers can effectively overcome the limitations of traditional static linear methods in dealing with nonlinearity, data noise, competitive ranking and optimisation solutions.

To verify model feasibility, we simulate four cathode material suppliers under industry benchmark data derived from Green Development Report of the Cathode Material Industry for New Energy 9 Vehicles in China and the industry energy efficiency benchmarks published by the International Energy Agency (IEA). We consider four cathode material suppliers: A, B, C, and D, Supplier A is an industry leader with 80 % clean energy, Supplier B is a small and medium-sized manufacturer with a more outdated process, Supplier C is a foreign-funded company with full qualifications, and Supplier D is an emerging company with strong innovative technology. Each supplier has three indicators: carbon efficiency, emission reduction technology, and green certification. Through the DHNN-AHP evaluation model, we calculate the comprehensive score and responsibility sharing ratio of each supplier.

Based on the carbon footprint of each stage of the product life cycle and the data collection sources of each indicator in Table 2, we calculate the carbon footprint share of the four cathode material suppliers A, B, C, and D based on the amount of raw materials provided by the suppliers and their carbon intensity, using the ratio of the average monthly carbon emission to the total carbon emission of the supply chain, which is 33 %, 21 %, 24 %, and 22 %, respectively. As shown in the raw data in Table S1 and the standardised data of Table S2 in the Supplementary Materials, we calculated each supplier's responsibility percentage according to the comprehensive score and carbon footprint share, and then recalculated each supplier's responsibility percentage according to the comprehensive score and carbon footprint share.

Table 2

Data collection

Indicator category	Secondary indicators	Specific meaning	Unit	Data source
Carbon efficiency	Unit carbon emission	The amount of CO_2 emitted per 10,000 yuan of output value created, reflecting the level of energy efficiency in production.	tonnes of CO_2 per 10,000 yuan (negative indicator, the smaller the value, the better) (tonne = 10^6 g)	Corporate Environmental Report (Public disclosure)
	Clean energy ratio	Proportion of renewable energy (solar, wind, etc.) in total energy consumption, reflecting the cleanliness of energy structure	Percentage % (positive indicator)	Energy Audit Report (Public disclosure)
Emission reduction technology	Carbon capture investment	Annual capital investment in carbon capture, utilisation and storage (CCUS) and other emission reduction technologies	million Yuan/year (positive indicator)	Financial data
	Process innovation	Effectiveness of green innovation in production processes, such as low-carbon process modification, waste recycling technology, etc., as measured by number of patents	Number of patents (positive indicator)	Intellectual Property Office
Green certification	ISO certification level	Environmental management system certification level (e.g. ISO 14001), divided into „no certification”, „basic certification” and „advanced certification”.	Grading (0 = none, 1 = basic, 2 = advanced)	Certificates
	Carbon label level	PCF certification level (e.g. „Bronze”, „Silver”, „Gold”), reflecting the full life cycle carbon performance of the product.	Grading (1 = Bronze, 2 = Silver, 3 = Gold)	Carbon labelling platform

After these raw data are calculated according to the steps of the DHNN-AHP fusion algorithm, they still need to be normalised and weighted to be converted into the supplier's comprehensive score, and the normalised results of the inverse of each supplier's score and the proportion of each supplier's un-normalised responsibility are further calculated, and the final 'Apportionment Difference' obtained shows the deviation between the responsibility allocation and the actual carbon footprint share.

Results and discussion

The detailed evaluation results are shown in Table S3 in the Supplementary Materials, we present the data using the intuitive radar chart in Figure 3 and the bar chart in Figure 4.

As shown in Figure 3, the performance characteristics of the suppliers are distinctly differentiated, and the overall scores of the four cathode material suppliers exhibit a clear gradient distribution: Supplier C (0.408) > Supplier A (0.357) > Supplier B (0.137) > Supplier D (0.098). This ranking accurately reflects each supplier's actual performance in the three dimensions of carbon efficiency, emission reduction technology, and green certification. Supplier A maintains an absolute advantage in the green certification dimension (0.714), exceeding other suppliers by at least 0.428 standardised units. Supplier B demonstrates balanced performance across all dimensions but remains overall low, with a comprehensive score (0.137) equivalent to only 33.6 % of the top-performing Supplier C.

Supplier C achieves the highest evaluation due to its superior carbon efficiency (0.497), while Supplier D ranks last due to under performance across all dimensions.

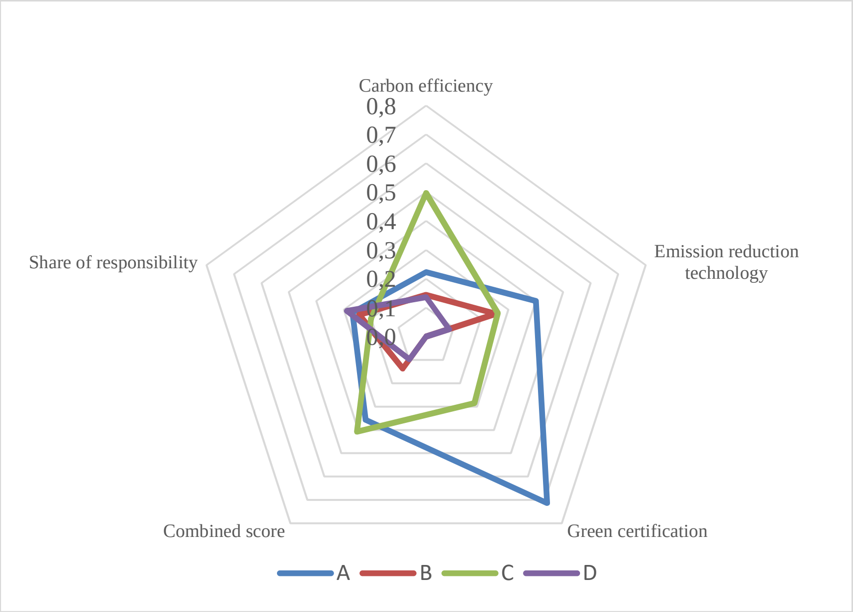

Fig. 3. Supplier performance radar

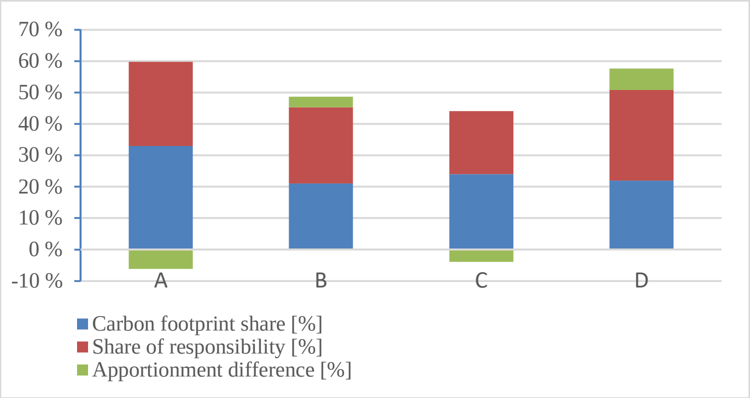

Fig. 4. Carbon footprint share vs responsibility ratio comparison

The differences between carbon shares and responsibility proportions illustrated in Figure 4 fully demonstrate the fairness and incentivising nature of the model. Suppliers A and C, as high performers, have responsibility proportions (26.81 % and 20.04 %) lower than their respective carbon footprint shares (33 % and 24 %), receiving responsibility reductions of 6.19 % and 3.96 %, respectively. Conversely, the lower-performing suppliers B and D have responsibility proportions (24.33 % and 28.83 %) exceeding their carbon footprint shares (21 % and 22 %), bearing additional responsibilities of 3.33 % and 6.83 %, respectively. The maximum difference in responsibility reaches ±6.83 %, significantly higher than the differentiation achieved by traditional methods.

Sensitivity and robustness

To ensure the robustness of the emission reduction responsibility allocation model proposed in this study and to verify the rationality of the parameter settings, this section conducts sensitivity and robustness analyses on the key parameters in the responsibility allocation formula (equation (8)) - the industry benchmark coefficient α and the adjustment coefficient β. We set three representative parameter scenarios for comparison: Scenario 1 has α = 0.8 and β = 0.2, which assigns a higher weight to historical carbon footprints, emphasising the principle of 'who pollutes, who is responsible.' Scenario 2 is the baseline scenario used in this study, with α = 0.7 and β = 0.3, balancing historical responsibility with future incentives. Scenario 3 has α = 0.6 and β = 0.4, which increases the penalty for suppliers with poor low-carbon performance, focusing more on an incentive-oriented approach of 'rewarding excellence and punishing shortcomings'. The results are shown in Table 3.

Table 3

Comparison of responsibility ratios under different parameter scenarios

Supplier	**Share of responsibility [%]**			**Ranking**
	$\boldsymbol{\alpha = 0.8, \beta = 0.2}$	$\boldsymbol{\alpha = 0.7, \beta = 0.3}$	$\boldsymbol{\alpha = 0.6, \beta = 0.4}$	
A	28.95	26.81	24.67	2
B	22.26	24.33	26.40	3
C	21.36	20.04	18.72	4
D	27.43	28.83	30.21	1

Under the three parameter scenarios, the ranking results of the suppliers' responsibility proportions from highest to lowest are completely consistent, with the order being: D > B > A > C. This result indicates that whether decision-makers lean toward the historical responsibility principle or the performance incentive principle, the model's assessment of the relative responsibilities of the four suppliers remains stable and unchanged. Meanwhile, although the ranking is stable, the specific values of responsibility proportions vary systematically with the parameters, in line with theoretical expectations. When α increases, the responsibility proportion of Supplier A, which has the highest carbon footprint share, rises, whereas the responsibility proportion of Supplier D, which has the lowest carbon footprint share but the poorest performance, decreases. Conversely, when β increases, the responsibility proportion of Supplier D, with the lowest composite score, rises significantly, while that of Supplier C, which performs best, further decreases. Supplier B, with a moderate carbon footprint share but a relatively low composite score, consistently bears substantial responsibility second only to Supplier D in all scenarios.

These findings demonstrate that the model's output is insensitive to changes in parameters α and β, highlighting the robustness of its core conclusions. The selection of benchmark parameters (0.7, 0.3) represents a reasonable policy-level balance, allowing supply chain managers to adjust parameter weights within a certain range according to different regulatory orientations or strategic objectives, without concern for disruptive changes in the ranking results.

Conclusion

Theoretical contribution - Our research provides a structured and actionable framework that leverages PLM data infrastructure, integrating a dynamic assessment mechanism through the DHNN-AHP model. This synergy achieves complete carbon traceability across all lifecycle stages and facilitates adaptive responsibility allocation, providing core enterprises with a transparent, data-driven carbon management and supplier assessment toolkit. The proposed DHNN-AHP model improves traditional supplier evaluation methods through dynamic weight adjustment and nonlinear optimisation, effectively addressing the rigidity issues of conventional static weight systems.

Managerial implications - Under the overarching “dual carbon” strategic goals, enterprises across the entire supply chain - including raw material suppliers, manufacturing entities, logistics providers, and brand owners - are facing increasing pressure to transition to low-carbon operations. This transformation is not only regulatory but also represents a fundamental reconfiguration of value creation centred around sustainability and carbon responsibility. This study verifies the effectiveness of the proposed model in achieving precise traceability, scientific evaluation, and equitable distribution, providing core enterprises in the supply chain with a quantifiable decision-making tool to implement the “dual carbon” goals.

Limitations - There are shortcomings in the paper that warrant further exploration in the future. The data in the article is based on the pilot experience of simulated values and still requires the introduction of actual data for further verification in the future. And the current model does not explicitly incorporate external policy variables such as carbon taxes, subsidies, or compliance incentives, which are critical in real-world decision-making environments.

Future work - Future research will focus on the promotion and application of the model in practical industrial settings, as well as its integration mechanisms with policies such as carbon tariffs. Firstly, combining blockchain technology with existing PLM-based traceability systems can further enhance the invariability and transparency of carbon data flows. Secondly, validating the model through an extensive multi-industry dataset and a larger supplier network will strengthen its generalisability and robustness. Finally, establishing a coordination mechanism between the proposed framework and emerging carbon border adjustment policies (such as CBAM) is crucial for aligning corporate-level carbon accountability with international climate governance and trade standards.

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