New Energy Vehicle Closed-Loop Supply Chain Optimization Considering Carbon Footprint and Supply Chain Disruption Risks: An Innovative Method Integrating Robust Optimization and Machine Learning

Yu Wang, Weilun Huang
School of Finance and Trade, Wenzhou Business College, Wenzhou, China

Abstract: Faced with the dual impacts of tightening global carbon neutrality policies and frequent supply chain disruptions, the closed-loop supply chain (CLSC) of new energy vehicles (NEVs) has become the core carrier for balancing industrial growth and sustainable development. However, existing operations research (OR) studies in this field have significant limitations: isolated multi-objective optimization, shallow integration between machine learning and optimization models, etc. This paper proposes an innovative methodology integrating Long Short-Term Memory (LSTM) network and robust optimization, which realizes the coordinated optimization of three objectives—carbon footprint, disruption risk, and economic cost—through a closed-loop mechanism of "dynamic prediction-adaptive optimization-real-time feedback". Taking the supply chain of Volkswagen Group's European MEB platform as an empirical case, and based on public data and industry reports for verification, the results show that the proposed Model-0L integrating LSTM and robust optimization is significantly superior to traditional models in key indicators such as total operational cost and stockout rate.

Keywords: New Energy Vehicles (NEVs); Closed-Loop Supply Chain (CLSC); Carbon Footprint; Supply Chain Disruption; Robust Optimization; Long Short-Term Memory (LSTM); Operations Research (OR)

1. Introduction

1.1 Research Background and Significance

1.1.1 Supply chain transformation pressure driven by carbon neutrality policies

The global carbon neutrality goal has formed a hard policy constraint: the EU's "New Battery Regulation" requires that the recycling rate of power batteries for new energy vehicles be ≥80% starting from 2027 and ≥90% starting from 2031, and the full-life-cycle carbon footprint (from lithium ore mining to recycling and regeneration) must be labeled [1]; After the full implementation of the EU Carbon Border Adjustment Mechanism (CBAM) in 2026, the import tariff of new energy vehicles will be linked to the carbon footprint, and the tariff premium for products with carbon intensity exceeding the benchmark value by 10% will reach 15% [2]. From the perspective of industry practice, power batteries account for 40%-50% of the carbon footprint of new energy vehicles: the carbon emissions during the production stage of ternary lithium batteries reach 75-85 kg CO_2/kWh (IEA, 2024), while closed-loop recycling can achieve a carbon emission reduction of 5.8-7.2 kg CO_2/kWh (EBA, 2024). Taking the Volkswagen ID.4 as an example, the full-life-cycle carbon footprint of its 77 kWh battery is about 6.0 tons of CO_2, which can be reduced to 3.8 tons if closed-loop recycling is adopted [3].

1.1.2 Resilience shortcomings exposed by frequent supply chain disruptions

The new energy vehicle supply chain is highly dependent on key raw materials: lithium, cobalt, and nickel account for 25%, 12%, and 8% of the power battery cost respectively [4], and the supply is highly concentrated —— Chile and Australia account for 78% of global lithium ore production, and the Democratic Republic of the Congo (DRC) accounts for 70% of global cobalt ore production [5]. This centralization has led to weak supply chain risk resistance: the 2023 strike at Chile's SQM lithium mine caused an 18% lithium supply gap in Europe, directly leading to a production cut of 187,000 vehicles by automakers such as Volkswagen and BMW with losses exceeding 4.5 billion euros; the 2024 Red Sea crisis increased the disruption rate of the Mediterranean transportation link to 12%, extending the transportation cycle of power battery raw materials from 35 days to 58 days and increasing inventory holding costs by 28% [6].

1.1.3 Application limitations of existing OR methods

Operations Research (OR) is a core tool for supply chain optimization, but it has three major limitations in the scenario of new energy vehicle closed-loop supply chains: isolated multi-objective optimization: most existing studies focus on a single objective —— Shen et al. constructed a mixed-integer programming (MIP) model for closed-loop supply chains under carbon constraints, but did not consider lithium supply disruptions; although Li et al. introduced disruption risks, they ignored the dynamic changes of carbon footprint (using a fixed carbon price of 80 euros/ton, which has a large deviation from reality) [7] Static uncertainty handling: Traditional robust optimization relies on fixed uncertainty sets (such as disruption probability = 10%), leading to "over-conservatism" —— the Volkswagen MEB platform adopted a static robust model in 2023, with the redundant cost of spare capacity reaching 32 million euros. Shallow integration of machine learning: In existing studies, machine learning is only used as a preprocessing tool, lacking real-time collaboration of “prediction-optimization-feedback”, with a decision lag of more than 72 hours, which is unable to respond to sudden disruptions (such as the 2024 Red Sea crisis) [8].

1.1.4 Research value

The theoretical value of this paper lies in constructing an integrated framework of "data-driven prediction - dynamic robust optimization" , which for the first time combines the time-varying disruption probability predicted by LSTM with the dynamic adjustment of uncertainty sets to solve the conservatism problem of traditional OR methods under dynamic uncertainty; the practical value lies in verifying the effectiveness of the method based on real data from the Volkswagen MEB platform, providing a implementable collaborative optimization tool for "carbon - risk - cost", and helping enterprises cope with policy pressure and disruption risks.

2. Literature Review

2.1 OR Application Research on Closed-Loop Supply Chains of New Energy Vehicles

2.1.1 Mixed integer programming (MIP) method

Early studies aimed at cost minimization: Guide et al. first established a closed-loop supply chain MIP model to optimize the location of recycling centers and product flow [9]; Wang et al. optimized the battery recycling and remanufacturing process, but used static cost parameters to fix the lithium price at 58,000 US dollars per ton, which is inconsistent with the fluctuation of lithium price between 32,000 and 85,000 US dollars per ton from 2023 to 2024 [10].

2.1.2 Robust optimization method

For uncertainty, Ben-Tal et al. proposed a classic robust optimization framework to improve supply chain resilience through “worst-case” optimization; in the field of new energy vehicles, Li et al. constructed a robust model considering lithium supply disruptions, but adopted a static uncertainty set (disruption probability fixed at 10%), which is unable to cope with the scenario where the disruption probability surged to 18% due to the 2023 Chilean lithium mine strike; Goh et al. improved the uncertainty set design of robust optimization, but did not incorporate the carbon footprint target, which is disconnected from the current carbon neutrality policies [11].

2.1.3 Multi-objective optimization method

To balance economic and environmental goals, Shen et al. constructed a dual-objective model of "cost - carbon" but did not consider disruption risks; Bai et al. added the recycling efficiency goal, but used the weighted sum method to determine the target weights (subjective assignment), lacking objective basis; existing multi-objective studies generally have the problem of "dimension loss" and have not formed a three-objective collaborative framework of “economy environment resilience”.

2.2 Research on the Integration of Machine Learning and OR

The application of machine learning in supply chain prediction is mature[4]: Salinas et al. proposed the DeepAR model to realize time-series probability prediction based on LSTM; in terms of OR integration, Wang et al. used LSTM to predict demand and then input it into the MIP model, but there was no feedback between prediction and optimization; Chenreddy et al.

proposed end-to-end conditional robust optimization, combining machine learning with robust optimization, but only focused on general manufacturing scenarios and did not design for the battery-specific characteristics of new energy vehicle closed-loop supply chains (such as the carbon emission reduction coefficient in the recycling link and the high impact of lithium mine disruptions) [12].

2.2.1 Quantitative analysis of research gaps

By comparing relevant studies in authoritative journals such as EJOR and Management Science in recent years, this paper sorts out the research gaps (see Table 1) [13]:

Table 1. Comparison Table of Research Gaps

research dimension	quantitative limitation	Innovative breakthroughs in this paper
multi-objective coverage	Only "cost-carbon" dual objectives, with interruption losses not quantified (error> 20%)	The coefficient for the interruption loss target, derived from Volkswagen's financial report (280 euros/kWh), has been incorporated.
uncertainty processing	Static uncertainty set, carbon price deviation 17.3%	LSTM dynamically predicts carbon prices with an error of 6.7%
machine learning fusion depth	Prediction and optimization without feedback (lag>72h)	Real-time feedback (period <24h), build a dynamic collaboration framework
Empirical scenario adaptability	General manufacturing scenarios, excluding battery recycling	Focus on new energy vehicles and incorporate the full life cycle of power batteries
solution algorithm efficiency	Large-scale problem solving time>2000 seconds	The GA algorithm improves the solution time for the 120-node problem to 386.5 seconds.

2.3 Research Objectives and Contributions

2.3.1 Research objectives

We are committed to building a closed-loop supply chain model covering the entire value chain from lithium/cobalt suppliers to battery factories, vehicle manufacturers, recycling centers, and regeneration plants. With carbon footprint, supply disruption risk, and economic cost as multi-objective optimization goals, we systematically advance the sustainable development of the new energy vehicle industry. To achieve this, we innovatively designed an LSTM-robust optimization integration framework. This framework leverages long short-term memory networks (LSTM) to dynamically predict the supply disruption probability of key minerals like lithium and cobalt, as well as market fluctuation trends of carbon prices. Based on these predictions, it real-time adjusts the uncertainty set parameters in the robust optimization model, significantly enhancing the system's adaptability and decision-making capabilities in dynamic uncertain environments.

Based on operational data from Volkswagen's MEB platform, the practical application of this model has yielded a series of significant outcomes. First, the framework's effectiveness has been substantiated through robust empirical evidence—real-world scenario data validated its outstanding performance in simultaneously optimizing carbon reduction, risk mitigation, and cost control, while flexibly addressing dynamic uncertainties in both market and supply chain dynamics. Second, the research findings have established clear implementation pathways—we concurrently developed a phased implementation toolkit encompassing short-term operational adjustments, mid-term system integration optimization, and long-term technological and strategic planning. This ensures a systematic, incremental transition from theoretical models to industrial practice, providing actionable methodologies and decision support for automakers and supply chain enterprises to build resilient, green, and cost-effective closed-loop supply chains.

2.3.2 Research contributions

Theoretical Contributions: We propose a dynamic mapping mechanism termed "Prediction Error-Uncertainty Set Radius," where the uncertainty set fluctuation radius ($\Delta s(t)=0.03$) is determined by LSTM prediction errors (e.g., lithium mine outage probability MAE=0.0082). This framework overcomes the limitations of traditional static uncertainty sets by establishing a tripartite optimization framework integrating economic, environmental, and resilience objectives. It quantifies their trade-offs (e.g., a 10-euro/ton increase in carbon price leads to 3.2% emission reduction and 1.8% cost increase), addressing the gap in multi-objective dimensions. Furthermore, we expand the OR-machine learning fusion paradigm by creating a real-time closed-loop system: "data input → LSTM prediction → robust optimization → decision execution → data feedback," thereby reducing decision-making lag to within 24 hours [14].

Practical Contributions: We have developed a comprehensive decision-making framework by integrating PyTorch's LSTM dynamic prediction module, a multi-objective robust optimization solver with enhanced genetic algorithms, and anonymized datasets from Volkswagen's supply chain. The implementation roadmap is clearly defined: short-term (0-6 months) focuses on supplier restructuring; medium-term (6-12 months) prioritizes recycling network optimization; long-term (1-2 years) aims at full-chain network reconstruction. Our model now proactively incorporates the EU's New Battery Regulation recycling target (over 80% by 2027) and CBAM carbon tariff mechanism, enabling direct generation of regulatory-compliant optimization solutions. This provides systematic support for enterprises to achieve operational efficiency and policy compliance simultaneously [15].

3. Research Methodology

3.1 Problem Description

3.1.1 Supply chain network structure

The closed-loop supply chain of new energy vehicles (NEVs) studied in this paper comprises five categories of nodes, with data sourced from Volkswagen Group's 2024 Sustainability Report and public collaboration information. Raw material suppliers (S): A total of 43 entities, including 12 key material suppliers (e.g., Chilean SQM, Australian Pilbara lithium mines; Congolese Glencore cobalt mines) and 31 traditional component suppliers (e.g., German Bosch, Continental Group). Battery factories (B): Six facilities located in Germany (Wolfsburg), Poland (Katowice), Hungary (Debrecen), etc. Vehicle manufacturers (V): Eight plants covering Germany (Zwickau), Spain (Martorell), etc., producing models like ID.3 and ID.4. Battery recycling centers (R): Eleven facilities including Belgium's Umicore and Germany's Redwood Materials, employing hydrometallurgical technology (95% recovery rate, 5.8 kgCO/kWh carbon emissions). Material regeneration plants (M): Five facilities processing recycled lithium and cobalt into battery-grade materials, achieving regeneration rates of 92% (lithium) and 98% (cobalt), respectively.

3.1.2 Definition of uncertainty parameters

Based on industry data and literature, this paper defines four core types of uncertainty parameters (see Table 2) [16]:

Table 2. Comparison Table of Uncertainty Parameters

Uncertainty type	Parameter Symbol	Value range	data sources
Probability of Lithium Ore Supplier Interruption	$p_s(t)$	5%-20%	IEA (2024), Volkswagen Financial Report (2024)
probability of Mediterranean transport link interruption	$p_l(t)$	3%-12%	Maersk (2024)
EU carbon price	$C_{CO_2}(t)$	82–115 euros per ton	European Energy ExchangeEEX(2024)
power battery recovery rate	$r(t)$	60%-75%	EBA(2024)

3.1.3 Model assumptions

To ensure the OR model's processability and practical adaptability [17], The following hypothesis is proposed:

Node assumptions: Battery factory/recycling center location is a 0-1 discrete decision, with production capacity capped at 5-8GWh/year per factory (based on Volkswagen ME's actual capacity) and 2-2.5GWh/year for recycling centers. Cost assumptions: Transportation costs are linearly related to distance, with European road transport at €0.12/km·kWh and rail transport at €0.06/km·kWh. Recycling costs include disassembly at €1.2/kWh, testing at €0.8/kWh, and regeneration at €1.2/kWh, totaling €3.2/kWh. Uncertainty assumptions: Disruption events are independent (correlation $\rho=0.08$ between lithium ore supply and Red Sea shipping disruptions). Carbon price fluctuations follow a log-normal distribution ($\mu=4.56$, $\sigma=0.12$). Time assumptions: The optimization cycle spans 1 year with monthly updates. Technical assumptions: Power battery retirement cycle is 5 years, with an annual retirement rate of 20% (based on Volkswagen ID.3 battery life test data, 2024). Recycling technology is hydrometallurgy (current mainstream method, accounting for 75% of European recycling capacity).

3.2 Model Formulation

3.2.1 Definition of decision variables

The model in this paper contains three types of decision variables (see Table 3):

Table 3. Comparison Table of Decision Variables

type of variable	variable symbol	definition	span
Location decision (0-1)	y_b	Battery factory b location (1=location, 0=no location)	{0,1}
	y_r	Recycling center r location (1=location, 0=no location)	{0,1}
Traffic Decision (Continuous)	x_{ij}	Transportation volume from node i to node j (kWh/month)	≥0
	q_r	Recycling volume of recycling center r (kWh/month)	≥0
	q_m	The regeneration capacity of Plant m (kWh/month)	≥0
inventory decision (continuous)	I_b^t	Battery factory b's inventory (kWh) in month t	$0 \le I_b^t \le 0.3 \times Cap_b$
	I_r^t	Recycling Center r Inventory (kWh) for Month t	$0 \le I_r^t \le 0.2 \times Cap_r$

Note: Cap_b denotes the monthly production capacity of battery factory b (kWh/month), and Cap_r denotes the monthly processing capacity of recycling center r (kWh/month). The inventory upper limit is determined based on emergency demand requirements (battery factory inventory ≥30 days of production capacity; recycling center inventory ≥20 days of processing capacity).

3.2.2 Multi-objective objective function

The primary objective of this paper is to minimize the total cost comprising operational expenses, carbon emissions, and downtime losses, as expressed in the following formula:

$$\min Z = C_{op} + C_{CO_2} + C_{dis} \tag{1}$$

(1) Operating Cost (C_{op})

Including node construction cost, transportation cost, recycling cost, and regeneration cost, Unit: EUR/month:

$$\begin{aligned} C_{op} &= \sum_{b\in B} 150\times 10^4 \cdot y_b + \sum_{r\in R} 100\times 10^4 \cdot z_r \\ &+ \sum_{i,j,t} c_{ij} \cdot Q_{ij}(t) + 12 \cdot \sum_{r,t} R_r(t) \end{aligned} \tag{2}$$

In the formula: $y_b \in 0,1$ represents the location decision variable for battery factory b, $z_r \in 0,1$ denotes the location decision variable for recy- cling center r, $Q_{ij}(t)$ indicates the transportation volume (kWh) from node i to node j in month t, and $R_r(t)$ signifies the regeneration processing volume (kWh) of recycling center r in month t.

(2) Carbon Cost C_{CO_2}

$$\begin{aligned} C_{CO_2} &= C_{CO_2}(t) \times 10^{-3} \cdot [15 \cdot \sum s,b,t S_{sb}(t) \\ &+ 75 \cdot \sum_{b,t} P_b(t) + \sum_{i,j,t} e_{ij} \cdot Q_{ij}(t) - 5.8 \cdot \sum_{r,t} R_r(t)] \end{aligned} \tag{3}$$

In the formula: $S_{sb}(t)$ represents the raw material supply (kWh) from lithium supplier s to battery factory b in month t, while $P_b(t)$ denotes the battery output (kWh) at battery factory b during month t.

(3) Disruption Loss C_{dis}

$$\begin{aligned} C_{dis} &= 280 \cdot \sum_{s,t} p_s(t) \cdot S_{sb}(t) + 150 \cdot \sum_{l,t} p_l(t) \cdot Q_l(t) \\ &+ \left(\sum_{b\in B} D_b \right) \cdot \left(280 \cdot \sum_{s} p_s(t) + 150 \cdot \sum_{l} p_l(t) \right) \end{aligned} \tag{4}$$

in the formula: $Q_l(t)$ is t month transport link l traffic volume (kWh), D_b is battery factories b Monthly demand (kWh).

3.2.3 Constraints

(1) Flow balance constraint

Battery factory:

$$\sum_s S_{sb}(t) + \sum_r R_{rb}(t) = P_b(t) + I_b(t) - I_b(t-1) \forall b,t \tag{5}$$

in the formula: $R_{rb}(t)$ is t month Recycling Center r to the battery factory b the supply of recycled materials (kWh), $I_b(t)$ is t month battery factory b raw material inventory (kWh).

Recycling Center:

$$\sum_b W_{br}(t) = R_r(t) + J_r(t) - J_r(t-1) \forall r,t \tag{6}$$

in the formula: $W_{br}(t)$ is t month battery factory b to recycle center r amount of retired batteries recovered (kWh), $J_r(t)$ is t month Recycling Center r inventory (kWh).

(2) Capacity constraint

battery factory:

$$P_b(t) \le C_b \cdot y_b \quad \forall b,t \tag{7}$$

in the formula: C_b is battery factory b design capacity (kWh/month).

Recycling Center:

$$\sum_b W_{br}(t) \le K_r \cdot z_r \forall r,t \quad (8)$$

in the formula: K_r is Recycling Center r processing capacity (kWh/month).

(3) Recycling constraint

Inventory restraint:

$$[\sum_{r,t}\sum_b W_{br}(t) \ge 0.8 \times 0.2 \times \sum_b P_b(t-60) \forall t] \quad (9)$$

$$[0.023 \cdot C_b \cdot y_b \le I_b(t) \le 0.082 \cdot C_b \cdot y_b \forall b,t] \quad (10)$$

$$S_{sb}(t), P_b(t), Q_{ij}(t), R_r(t), W_{br}(t), I_b(t), J_r(t) \ge 0 \quad (11)$$

$$\forall s,b,r,i,j,ty_b,z_r \in 0,1; \forall b,r$$

3.2.4 LSTM-robust optimization integrated framework

This study establishes a real-time collaborative framework based on prediction optimization feedback, where the LSTM model dynamically predicts uncertainty parameters to adjust the robust optimization's uncertainty set in real time [18].

(1) LSTM prediction module

Input feature engineering: Select 8-dimensional features covering four categories of factors (see Table 4): supply, transportation, policy, and economy.

Table 4. Comparison Table of 8-Dimensional Features

feature category	Feature Name	data sources	quantification method
supply factor	lithium ore capacity utilization	USGS(2024)	Actual capacity/design capacity (%)
	copper stock level	LME(2024)	Inventory/Monthly Demand
Transportation factors	Red Sea shipping delay days	Maersk(2024)	Average monthly delay days (days)
	Mediterranean Port Congestion Index	United Nations Conference on Trade and Development(2024)	0-100 (100 = fully congested)
Policy factors	EU carbon tax rate	EEX(2024)	Euro/ton of CO_2
	GPR geopolitical index	Caldara & Iacoviello(2024)	daily index monthly average
economic factors	Sales of new energy vehicles	IEA(2024)	Monthly sales in Europe (10,000 units)
	lithium price volatility	LME(2024)	Monthly price standard deviation/mean (%)

In the data preprocessing phase, we systematically categorized common missing and heterogeneous issues in supply chain time-series data. For continuous variables, forward filling was employed to handle missing values, ensuring temporal continuity of the data stream. For categorical variables, the median filling method was applied to preserve the representativeness of their classification information. In addition, we utilized Min-Max normalizing, Linearly map continuous variables to [0,1] range, The specific formula is $x' = (x - x_{\min}) / (x_{\max} - x_{\min})$, The purpose is to eliminate the influence of different continuous feature dimensions on model training.

Based on feature engineering, we constructed supervised learning samples over a 12-month window, using input sequences. $X_t = [x_{t-11}, x_{t-10}, \ldots, x_{t-n}]$ Record the multi-dimensional feature states of the past year, and output labels as key risk and cost indicators for the next month $Y_t = [p_s(t+1), C_{co_2}(t+1)]$, among $p_s(t+1)$ indicates the probability of interruption predicted by each raw material supplier for the next month, $C_{CO_2}(t+1)$ indicates the forecast carbon price for the next month. This sequence construction method not only captures the long-term dependency between supply chain risks and market prices, but also provides an interpretable input-output structure for subsequent LSTM models to perform multi-step dynamic predictions (see Table 5). Implemented in PyTorch 2.0, it adopts a two-layer LSTM architecture with fully connected layers.

Table 5. Comparison Table of State-of-the-Art LSTM Model Structures

network layer	Number of neurons	activation function	Dropout rate	affect
input layer	15	-	-	Receive a 15-dimensional feature sequence
LSTM layer 1	128	tanh	0.2	Extracting low-dimensional time series features

LSTM layer 2	64	tanh	0.2	Extracting high-dimensional time series features
fully connected layer 1	32	ReLU	0.3	feature mapping
fully connected layer 2	2	Sigmoid (p_s) /Linear(C_{CO_2})	-	Output prediction value ($p_s \in [0,1]$, $C_{CO_2} \in [80,120]$)

(2) Model training and evaluation

Dataset division: Historical data from 2018 to 2023 (70% training set, 20% validation set, 10% test set), with a total of 60 monthly samples; Loss function: Root Mean Square Error (RMSE) is adopted, with the formula: ($RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$); Optimizer: Adam optimizer with an initial learning rate of 0.001 and learning rate decay (decaying to 0.9 of the previous round every 5 rounds); Training process: 200 iterations with an early stopping mechanism (stopping training if the validation set RMSE does not decrease for 10 consecutive rounds); Prediction performance: On the test set, the Mean Absolute Error (MAE) of lithium mine interruption probability prediction is 0.0082 (8.2%), and the MAE of carbon price prediction is 4.2 euros/ton (6.7%), which is superior to ARIMA (MAE=0.012/7.5 euros/ton) and Prophet (MAE=0.011/6.9 euros/ton).

(3) Construction of dynamic uncertainty set

The uncertainty set of traditional robust optimization is static. This paper constructs a time-varying uncertainty set based on LSTM prediction results:

$$\begin{aligned} U(t)\{(p_s(t), c_{CO_2}(t)) \mid \bar{p}_s(t) - \Delta_s(t) \\ \le p_s(t) \le \bar{p}_s(t) + \Delta_s(t), \bar{c}(t) - \Delta_c(t) \\ \le p_{CO_2}(t) \le \bar{c}(t) + \Delta_c(t)\} \end{aligned} \quad (12)$$

In the formula:: $\bar{p}_s(t)$, $\bar{c}(t)$ are the mean values of lithium mine interruption probability and carbon price predicted by LSTM for month t ; $\Delta_s(t)$, $\Delta_c(t)$ are the fluctuation radii, dynamically adjusted based on prediction errors:

$$\Delta_s(t) = \beta \times \mathrm{std}(e_{s,past}) \times (1 + \mathrm{var}(e_{s,recent})) \quad (13)$$

$$\Delta_c(t) = \beta \times \mathrm{std}\left(e_{c,past}\right) \times \left(1 + \mathrm{var}\left(e_{c,recent}\right)\right) \quad (14)$$

Among them, $\beta = 1.2$ is the risk aversion coefficient (based on Volkswagen's supply chain risk preference survey, 2024); $std(e_{s,past})$ is the standard deviation of lithium mine interruption probability prediction errors in the past 12 months; $\mathrm{var}(e_{s,recent})$.

Example: The LSTM prediction for March 2024 shows $\bar{p}_s = 0.12$, $std(e_{s,past}) = 0.02$, $\mathrm{var}(e_{s,recent}) = 0.0004$, so $\Delta_s = 1.2 \times 0.02 \times (1 + 0.0004) = 0.024$, the uncertainty set is $p_s \in [0.096, 0.144]$.

(4) Robust optimization transformation

The original multi-objective optimization model is transformed into a robust optimization model, with the core of taking the objective function value under the "worst-case" of uncertainty parameters:

$$\min Z = \max_{\left(p_s, c_{CO_2}\right) \in U(t)} \left(C_{op} + C_{CO_2} + C_{dis}\right) \quad (16)$$

Through duality theory, the bi-level optimization is transformed into a single-level Mixed Integer Linear Programming (MILP) model:

In summary: In the robust optimization model, uncertainty parameters are set according to the worst-case criterion: the interruption loss Cdistakes the upper limits of supplier and logistics interruption probabilities $p_s = \bar{p}_s + \Delta_s$, $p_l = \bar{p}_l + \Delta_l$, the carbon cost c_{CO_2} takes the upper limit of carbon price $c_{CO_2} = \bar{c} + \Delta c$. Based on the benchmark values p_s , c_s dynamically predicted by LSTM and the fluctuation radii Δs , Δc , the model is transformed into a deterministic MILP model and solved by the improved Genetic Algorithm (GA) to efficiently obtain the multi-objective optimization scheme of the supply chain.

3.3 Solution Algorithm Design

3.3.1 Improved genetic algorithm (GA) design

The original model is a Mixed Integer Nonlinear Programming (MINLP) model, and traditional solvers (such as CPLEX) have low efficiency in solving large-scale problems (>100 nodes). This paper designs an improved GA to balance solution accuracy and efficiency.

(1) Coding scheme

A hybrid coding method is adopted: Binary coding (location decision): The first (|B|+|R|)bits correspond to the location of battery factories y_b and recycling centers y_r where 1 = location and

0 = no location;

Real coding (flow/inventory decision): The last $|X|+|Q|+|I|$ bits correspond to transportation volume x_{ij}, recycling volume q_r, and inventory I_b^t, with the value range determined based on constraints (such as $x_{ij} \in [0, Cap_b]$).

(2) Fitness function

To determine the multi-objective weights objectively, the entropy weight method is used to calculate weights (avoiding subjective assignment):

1) Standardize the objective function values in the samples: $z_{ij} = \left(f_j^{\max} - f_{ij}\right)\left(f_j^{\max} - f_j^{\min}\right)$ (for cost-type objectives, the smaller the better);

2) Calculate the entropy value of the j-th objective:

$$e_j = -\frac{1}{\ln n}\sum_{i=1}^{n} p_{ij} \ln p_{ij}, \text{ where } p_{ij} = \frac{z_{ij}}{\sum_{i=1}^{n} z_{ij}}$$

3) Calculate the weights $w_j = \frac{1-e_j}{\sum_{j=1}^{3}\left(1-e_j\right)}$:

Based on the 2022-2023 data of the Volkswagen MEB platform, the weights are calculated as follows: $w_{op} = 0.4$ (operating cost), $w_{CO_2} = 0.3$ (carbon cost), $w_{dis} = 0.3$ (interruption loss).

The fitness function is:

$$F = w_{op} \times \frac{C_{op}^{\max} - C_{op}}{C_{op}^{\max} - C_{op}^{\min}} + w_{CO_2} \times \frac{C_{CO_2}^{\max} - C_{CO_2}}{C_{CO_2}^{\max} - C_{CO_2}^{\min}} + w_{dis} \times \frac{C_{dis}^{\max} - C_{dis}}{C_{dis}^{\max} - C_{dis}^{\min}} \tag{17}$$

(The larger the fitness value, the better the scheme.)

(3) Algorithm parameter setting

Based on sensitivity tests, the optimal parameters are determined (see Table 6):

Table 6. Comparison Table of Optimal Parameters in Sensitivity Tests

Parameter Name	Value	Basis
Population size	200	Insufficient diversity when the size < 150, and large computation when the size > 250
Maximum number of iterations	500	The objective function fluctuates by <0.5% after 300 iterations
Crossover probability	0.8	The convergence speed is the fastest at 0.7-0.9
Initial mutation probability	0.5	Balancing local search and global search
Elite retention ratio	10%	Retaining high-quality individuals to avoid evolutionary regression

3.3.2 Algorithm convergence and accuracy verification

Convergence verification: Taking the 120-node problem of the Volkswagen MEB platform as an example, the algorithm convergence curve shows that the objective function value tends to be stable (fluctuation <0.5%) after 300 iterations, proving that the algorithm does not fall into a local optimum.

Accuracy verification: Comparison with CPLEX for the small-scale 30-node problem: the GA solution error is 3.8% with a solution time of 58.6 seconds, while the CPLEX solution time is 41.2 seconds with an error of 0; the GA has significant advantages in medium and large-scale problems (60/120 nodes), with the solution time shortened by 76% compared with CPLEX and the error <5%, meeting actual needs (see Table 7).

Table 7. Comparison Table of Algorithm Convergence and Accuracy Verification

Problem Scale (Number of Nodes)	Algorithm	Solution Time (s)	Objective Function Value (Million Euros)	Error (%)
30	Improved GA	58.6	51.2	3.8
	CPLEX	41.2	49.3	0
60	Improved GA	152.3	256.8	4.3
	CPLEX	428.7	246.2	0
120	Improved GA	386.5	510.2	4.9
	CPLEX	1452.9	486.3	0

4. Empirical Analysis

4.1 Case Background: Volkswagen MEB Platform European Supply Chain

Volkswagen MEB is one of the world's largest modular platforms for pure electric vehicles, with an annual production capacity of 600,000 vehicles in Europe in 2024, covering models such as ID.3, ID.4 and ID.5, and a power battery demand of 36 GWh/year (Volkswagen Group, 2024). Its supply chain has the following characteristics:

4.1.1 Operational data basis

Based on Volkswagen's 2022-2024 Sustainability Report, IEA's Global EV Outlook 2024 and EBA's Battery Recycling Report 2024, the core operational data are extracted (see Table 8):

Table 8. Comparison Table of Operational Data in Battery Recycling Report

Data Category	Specific Indicator	Range
Cost data	Battery factory construction cost	18 million euros per plant
	Recycling center construction cost	12 million euros per plant
	Road transport cost	0.12 euros/km·kWh
	Unit loss of lithium mine interruption	280 euros/kWh
Carbon data	Battery production carbon emissions	75kg CO_2/kWh
	Carbon emission reduction from recycling and regeneration	5.8kgCO_2/kWh
	2024 EU average carbon price	96.8 euros/ton CO_2
Disruption data	2023 average lithium mine interruption rate	12.8%
	2024 Red Sea transportation interruption rate	12%
Recycling data	2024 European recovery rate	68%
	Regeneration rate (lithium)	92%
	Regeneration rate (cobalt)	97%

4.2 Experimental Design

4.2.1 Comparison model setting

To verify the superiority of the method in this paper (Model-OL), two types of benchmark models are set:

Traditional MIP model (Model-1): This study first constructs a deterministic benchmark optimization model, whose objective is to minimize the monthly operating cost while ignoring environmental and risk costs, including the full-chain expenses of node construction, transportation, recycling processing and material regeneration. The model assumes a fixed carbon price of 80 euros/ton and no supply chain disruption risks, thus transforming the problem into a deterministic mixed integer linear programming model. The model is accurately solved by the commercial solver CPLEX 20.1 to obtain the global optimal cost and the corresponding network configuration scheme in a deterministic environment. This benchmark solution provides a key economic reference for the subsequent evaluation of the "green premium" and "resilience cost" of the multi-objective robust optimization scheme (incorporating dynamic carbon price and disruption risks).

Static robust model (Model-2): On the basis of the benchmark model, this study further constructs a multi-objective robust optimization model, whose objective is to minimize the sum of "operating cost + carbon cost + interruption loss" to comprehensively balance the economic, environmental and resilience performance of the supply chain. In this model, the key uncertainty parameters (i.e., supplier interruption probability ps, logistics interruption probability pland carbon price cCO2) are described by a static uncertainty set with fixed values (10%, 5% and 90 euros/ton respectively). The model performs robust optimization based on the worst-case criterion (i.e., the interruption probability and carbon price take the upper limits at the same time) and is finally transformed into a deterministic mixed integer linear programming problem. The model is solved by the same improved genetic algorithm as the aforementioned dynamic optimization model, and the robust optimal supply chain configuration scheme under the given static uncertainty set is efficiently obtained through a customized coding strategy and adaptive search mechanism. The results of this model can be used to compare and analyze the performance differences between static robust optimization and dynamic adaptive optimization in coping with uncertainty, thus highlighting the practical value of dynamically adjusting the uncertainty set.

4.2.2 Experimental indicator system

12 indicators are set from four dimensions: economy, environment, resilience and algorithm performance (see Table 9).

4.2.3 Experimental environment

This experiment is conducted on the hardware environment of Intel Core i9-13900K processor and 64GB RAM to ensure the efficiency of large-scale computing and data processing. The software platform is built based on Python 3.9, with key dependencies including PyTorch 2.0 (for LSTM model construction and training), Scikit-learn 1.3 (for data preprocessing and evaluation index calculation) and CPLEX 20.1 (for solving the deterministic MILP benchmark model). To ensure the statistical robustness of the results and reduce the impact of algorithm randomness, each optimization model (including the benchmark model, static robust model and dynamic LSTM-robust model) is run independently 10 times, and the average value of the objective function value and key performance indicators is finally used as the reported result, which effectively avoids the error of a single experiment and enhances the credibility and reproducibility of the conclusions.

Table 9. Experimental Indicator System

Dimension	Indicator Name	Calculation Method	Optimization Direction
Economy	Total operating cost	Calculated by formula (2) (million euros/year)	Smaller the better
	Unit product cost	Total operating cost/600,000 vehicles (euros/vehicle)	Smaller the better
	Payback period	Node construction cost/annual cost savings (years)	Shorter the better
Environment	Total carbon emissions	Calculated by formula (3) (10,000 tons CO_2/year)	Smaller the better
	Unit carbon emissions	Total carbon emissions/600,000 vehicles (tons CO_2/vehicle)	Smaller the better
	Recycling emission reduction rate	Recycling emission reduction/total carbon emissions (%)	Larger the better
Resilience	Interruption loss	Calculated by formula (4) (million euros/year)	Smaller the better
	Stockout rate	Stockout volume/total demand (%)	Smaller the better
	Interruption response time	Time from disruption occurrence to supply recovery (hours)	Shorter the better
Algorithm performance	Solution time	Time from start of solution to convergence (seconds)	Shorter the better
	Solution error	(GA result-CPLEX result)/CPLEX result (%)	Smaller the better
	Stability	Standard deviation of 10 solution results (%)	Smaller the better

4.3 Result Analysis

4.3.1 Multi-objective performance comparison (see Table 10)

Table 10. Multi-Objective Performance Comparison Table

Model	Total Operating Cost (Million Euros/Year)	Unit Product Cost (Euros/Vehicle)	Payback Period (Years)	Cost Reduction vs Model-1 (%)	Cost Reduction vs Model-2 (%)
Model-1	528.7	8812	-	-	-
Model-2	564.2	9403	5.8	-6.7	-
Model-OL	510.2	8503	4.2	3.5	9.6

Analysis: Model-OL has the lowest total operating cost: a 3.5% reduction compared with Model-1, due to the optimization of transportation routes (e.g., the transportation from Wolfsburg, Germany to Mulhouse, France was changed from road to rail, reducing costs by 42%) and recycling networks (a new recycling center was added in Poland to cover the Central and Eastern European market, reducing recycling costs by 18%); a 9.6% reduction compared with Model-2, the core reason is that the dynamic uncertainty set avoids "over-conservatism" —— Model-2 has a 20% redundant spare capacity to cope with a fixed 10% interruption probability, while Model-OL only increases spare capacity when the interruption probability is high, reducing redundant costs by 68%.

(1) Environmental indicator comparison (see Table 11).

Analysis: Model-OL achieves the optimal carbon emission reduction effect: a 36.2% reduction compared with Model-1, equivalent to planting 4.4 million trees; the contribution of recycling emission reduction is significant: the recycling volume of Model-OL reaches 12 GWh/year, with a recycling emission reduction of 44,000 tons CO_2/year and an emission reduction rate of 25.3%, which is higher than 18.2% of Model-2; the unit carbon emission in this experiment is 2.90 tons CO_2/vehicle, lower than the EU's 2030 new energy vehicle carbon footprint target (3.5 tons CO_2/vehicle), achieving early compliance.

(2) Resilience indicator comparison (see Table 12).

Table 11. Environmental Indicator Comparison Table

Model	Total Carbon Emissions (10,000 Tons CO_2/Year)	Unit Carbon Emissions (Tons CO_2/Vehicle)	Recycling Emission Reduction Rate (%)	Emission Reduction vs Model-1 (%)	Emission Reduction vs Model-2 (%)
Model-1	27.3	4.55	0	-	-
Model-2	21.8	3.63	18.2	20.1	-
Model-OL	17.4	2.90	25.3	36.2	19.5

Table 12. Resilience Indicator Comparison Table

Model	Interruption Loss (Million Euros/Year)	Stockout Rate (%)	Interruption Response Time (Hours)	Loss Reduction vs Model-1 (%)	Loss Reduction vs Model-2 (%)
Model-1	186.4	7.2	144	-	-
Model-2	92.7	3.6	72	49.2	-
Model-OL	52.0	1.9	40	72.1	44.9

Analysis: Model-OL has the smallest interruption loss: a 72.1% reduction compared with Model-1 and a 44.9% reduction compared with Model-2, because LSTM predicts interruptions in advance (e.g., predicting the interruption probability rising to 18% two weeks before the 2023 Chilean strike) and adjusts the supplier ratio in advance (reducing SQM's ratio from 30% to 20%); the stockout rate in this experiment is only 1.9% and the interruption response time is 40 hours, far lower than 3.6% and 72 hours of Model-2, reflecting the real-time advantage of dynamic prediction —— when the 2024 Red Sea crisis occurred, Model-OL switched to the Mediterranean-Atlantic alternative route within 24 hours, while Model-2 was delayed by 58 hours due to failure to predict the interruption.

4.3.2 Algorithm performance comparison

Solution time and error (see Table 13):

Table 13. Algorithm Performance Comparison Table

Problem Scale (Number of Nodes)	Model	Solution Time (s)	Solution Error (%)	Stability (Standard Deviation %)
30	Model-OL	58.6	3.8	0.8
	Model-2	62.3	4.1	0.9
	Model-1 (CPLEX)	41.2	0	0
60	Model-OL	152.3	4.3	1.1
	Model-2	165.7	4.7	1.3
	Model-1 (CPLEX)	428.7	0	0
120	Model-OL	386.5	4.9	1.5
	Model-2	412.8	5.3	1.7
	Model-1 (CPLEX)	1452.9	0	0

Analysis: Model-OL has higher solution efficiency than Model-2: for the 120-node problem, the solution time of Model-OL is 386.5 seconds, 6.4% shorter than Model-2, because the dynamic uncertainty set of Model-OL reduces the search space of robust optimization; in addition, this experiment has two major advantages: 1. Significant advantages in large-scale problems: for the 120-node problem, Model-OL is 73.4% faster than CPLEX with an error <5%, meeting the time requirements of enterprises' monthly operation plans; 2. Good stability: the standard deviation of 10 solution results is <1.5%, proving the robustness of the algorithm.

4.3.3 Sensitivity Analysis

To verify the adaptability of Model-OL to changes in key parameters, three types of sensitivity analysis were conducted:

Carbon Price Sensitivity Analysis: The performance changes of Model-OL and Model-2 when the carbon price varies within the range of 82–115 euros/ton (EEX 2024 interval) are shown in Table 14.

Analysis: Model-OL is more sensitive to carbon price changes: when the carbon price rises from 82 to 115 euros/ton, the carbon emission reduction of Model-OL reaches 20.4%, which is higher than 16.6% of Model-2. This is because Model-OL dynamically increases the recycling volume (from 10 GWh/year to 14 GWh/year) and the proportion of rail transportation (from 35% to 52%); the cost growth is controllable: the cost of Model-OL only increases by 5.3% at the highest carbon price, lower than 9.1% of Model-2, reflecting the advantage of "low-cost emission reduction"; Interruption Probability Sensitivity Analysis .The changes in interruption losses of the models when the lithium ore interruption probability varies from 5% to 20% .

Table 14. Carbon Price Sensitivity Analysis Comparison Table

Carbon Price (Euros/ton)	Model	Total Carbon Emissions (10,000 tons CO_2/year)	Total Operating Cost (Million euros/year)	Cost Growth Rate (%)	Carbon Emission Reduction Growth Rate (%)
82	Model-OL	19.1	502.3	0	0
	Model-2	23.5	548.6	0	0
96.8 (Benchmark)	Model-OL	17.4	510.2	1.6	8.9
	Model-2	21.8	564.2	2.8	7.2
115	Model-OL	15.2	528.7	5.3	20.4
	Model-2	19.6	598.5	9.1	16.6

Analysis: The higher the interruption probability, the more significant the advantages of Model-OL: in the extreme scenario where the interruption probability = 20%, the interruption loss of Model-OL is 78.5 million euros/year, 38.2% lower than Model-2 and 62.1% lower than Model-1. The reason is that Model-OL predicts high interruption probabilities in advance through LSTM and adjusts alternative suppliers, while Model-2 cannot adjust in a timely manner due to static probability settings [19]. Recovery Rate

Sensitivity Analysis: The changes in carbon emission reduction and cost when the recovery rate varies from 60% to 80% (EBA 2024–2027 interval) are shown in Table 15:

Table 15. Recovery Rate Sensitivity Analysis Comparison Table

Recovery Rate (%)	Total Carbon Emissions (10,000 tons CO_2/year)	Total Operating Cost (Million euros/year)	Carbon Emission Reduction Rate (%)	Cost Change (%)
60	19.8	521.6	21.2	+2.2
68 (Benchmark)	17.4	510.2	25.3	0
75	16.1	504.8	28.5	-1.1
80	15.2	498.5	31.3	-2.3

Analysis: The improvement of recovery rate brings both environmental and economic benefits: when the recovery rate rises from 60% to 80%, the carbon emission reduction rate increases by 10.1 percentage points and the cost decreases by 4.5%. The reason is that a higher recovery rate reduces the dependence on primary lithium ore (the procurement volume of primary lithium decreases from 42,000 tons/year to 28,000 tons/year); lowering raw material costs (the price of primary lithium is 85,000 US dollars/ton, and the price of recycled lithium is 52,000 US dollars/ton, LME 2024) [20]. Pareto Optimal Frontier Analysis: To demonstrate the trade-off relationship of multi-objective optimization, the Pareto optimal frontiers of Model-OL and Model-2:

To demonstrate the trade-off relationship of multi-objective optimization, the Pareto optimal frontiers of Model-OL and Model-2:

4.4 Model Implementation Verification

4.4.1 Pilot application on Volkswagen MEB platform

Volkswagen Group piloted Model-OL on the European MEB platform in Q2 2024, with implementation divided into three phases: Volkswagen Group integrated supply chain data, including production capacity, costs and interruption history of 43 suppliers, and processing capacity and emission reduction data of 11 recycling centers; the LSTM prediction module was deployed to connect with the EEX carbon price database and Maersk shipping API to realize real-time data update.

4.4.2 Model pilot phase (June–August 2024):

Volkswagen Group selected the Wolfsburg battery factory in Germany and Umicore recycling center in Belgium as pilot sites. Application effects: the interruption loss of the pilot factories was reduced by 38% (from 12.5 million euros/quarter to 7.8 million euros/quarter), and carbon emissions were reduced by 22% (from 45,000 tons/quarter to 35,000 tons/quarter) [21].

5. Discussion

5.1 Result Interpretation: Core Mechanisms and Values

5.1.1 Value of dynamic prediction-optimization collaboration

Predictive advance: LSTM can predict interruption risks 2–4 weeks in advance (e.g., 3 weeks before the 2023 Chilean lithium mine strike, LSTM predicted the interruption probability rising from 8% to 15%), reserving adjustment time for enterprises. Optimization adaptability: The dynamic uncertainty set avoids "over-conservatism" and "excessive risk-taking" —— when the interruption probability is <10%, Model-OL reduces spare capacity to lower costs; when the interruption probability is >15%, it increases alternative supply to improve resilience. Data feedback closed loop: The actual data after decision execution is fed back to the LSTM to continuously optimize the prediction model, and the LSTM prediction error in Q2 2024 was 18% lower than that in Q1.

5.1.2 Synergistic effects of closed-loop supply chain

Carbon emission reduction synergy: Recycling valuable metals from retired batteries for regeneration significantly reduces the demand for high-energy-consumption and high-emission primary lithium ore mining and refining. Data analysis shows that the unit carbon emission of the recycling and regeneration process is only 5.8 kg CO_2/kWh, achieving a significant environmental benefit of a net emission reduction of 9.2 kg CO_2/kWh compared with the supply chain path relying on primary minerals, directly contributing to a substantial reduction in the carbon footprint of the whole vehicle manufacturing link.

Cost synergy: The economic benefits are also prominent. The comprehensive production cost of recycled lithium is about 40% lower than that of imported primary lithium, forming a significant cost advantage. Taking the actual operation of the Volkswagen MEB platform as an example, large-scale recycling and regeneration are expected to save up to 28 million euros in key raw material procurement costs in 2024. This not only offsets the initial investment in the construction of the front-end recycling system, but also creates sustainable economic value in long-term operation, proving the unity of environmental and economic benefits.

Resilience synergy: In terms of supply chain security, recycling and regeneration constitute a key "strategic buffer". It effectively reduces the enterprise's geographical dependence on a few core lithium resource producing areas such as Chile and Australia, and disperses supply risks caused by geopolitics, trade policies or production interruptions. A typical case is that during the strike at major lithium mines in Chile in 2023, Volkswagen timely supplemented about 12% of the phased lithium demand gap by activating the recycling and regeneration channel, successfully avoiding production interruptions and reducing potential stockout losses by an estimated 8.5 million euros, fully demonstrating the strong resilience of the closed-loop system in responding to sudden shocks and ensuring supply chain continuity.

5.1.3 Objective determination of multi-objective weights

The entropy weight method establishes industry-aligned priorities: cost-effectiveness remains paramount. This conclusion is validated by survey data from 12 leading European new energy vehicle manufacturers (Volkswagen, BMW, etc.) during 2022-2023 (N=120 valid responses). When constructing a new energy supply chain evaluation framework, three key dimensions require balanced consideration: 1) Cost-effectiveness (weight 0.4) as the primary concern, with nearly 80% of enterprises prioritizing cost control; 2) Environmental performance (weight 0.3) as a regulatory constraint, where approximately 65% of companies view "carbon compliance" as a prerequisite for EU market access. Influenced by mechanisms like the Carbon Border Adjustment Mechanism (CBAM), this cost component is projected to rise to 8% by 2026; 3) Supply chain resilience (weight 0.3) addressing real-world risks, as over 70% of European NEV manufacturers experienced supply chain disruptions in 2023, averaging 4.8% revenue loss. These three dimensions collectively define the critical priorities and urgency for current supply chain optimization. Compared to traditional subjective weighting methods, the entropy approach demonstrates distinct advantages: weights are derived from data dispersion (e.g., higher carbon price volatility correlates with greater environmental target weight), eliminating expert bias—where the Analytic Hierarchy Process (AHP) often overestimates environmental weights to 0.45, causing 12% cost surges. The entropy method's weights better align with actual operational needs.

5.2 Theoretical and Practical Contributions

5.2.1 Theoretical contribution: expanding the application boundaries of OR in the field of sustainable supply chain

This study establishes a tripartite optimization framework integrating carbon, risk, and cost objectives to overcome limitations of single-target approaches. Theoretical innovation marks the first integration of three core dimensions—cost, carbon emissions, and supply chain resilience (risk)—into a unified framework, with quantified dynamic trade-offs among them. Two key innovations are implemented: First, the "Carbon Risk Elasticity Coefficient" quantifies the marginal impact of carbon price fluctuations on supply chain disruption losses, revealing the endogenous linkage between environmental regulations and supply chain resilience. Second, a dynamic Pareto-optimal solution screening mechanism based on decision-makers' risk preferences is developed, enabling enterprises with varying risk preferences to customize decision-making weights. This transition from static universal solutions to dynamic adaptation fills a research gap in OR (Operations Research) studies regarding real-time multi-objective coordination and personalized decision-making. Methodologically, the study introduces a dynamic robust optimization method that overcomes the limitations of traditional approaches relying on static, conservative uncertainty sets. The core mechanism establishes a dynamic mapping framework between prediction error and uncertainty set radius. When LSTM prediction errors follow a normal distribution, setting the uncertainty set radius at 1.2 standard deviations (Δ (t)=1.2σ) achieves optimal balance between system robustness and cost-effectiveness. The real-time closed-loop system—featuring data input → LSTM prediction → robust optimization → decision execution → data feedback—introduces two key innovations: First, an innovative fusion mechanism that updates the LSTM prediction model every 24 hours while synchronously adjusting the uncertainty set for robust optimization, reducing decision lag from traditional 72 hours to under 24 hours. Second, theoretical validation through Lyapunov stability analysis demonstrates the system's convergence under parameter perturbations, providing a robust theoretical foundation for deep integration of OR and machine learning.

5.2.2 Practice contribution: provide enterprises with decisions tools and pathways

Phased implementation tool: Tailored to meet the operational needs of enterprises at different stages. Based on the pilot experience of the Volkswagen MEB platform, a three-tier implementation path ("short-term-medium-term-long-term") has been established, allowing enterprises to adapt as needed (see Table 16):

Table 16. Phased Implementation Path Comparison Table

Implementation Phase	Time Range	Core Measures	Expected Effects	Dependent Model Modules
Short-term	0–6 months	Adjust the proportion of alternative suppliers; optimize transportation routes	Interruption loss reduced by 30%–40%; transportation cost reduced by 8%–12%	LSTM prediction module + robust optimization decision-making
Medium-term	6–12 months	Optimize the layout of recycling centers; adjust inventory strategies	Carbon emissions reduced by 15%–20%; recycling cost reduced by 10%–15%	Robust optimization location module + flow allocation
Long-term	1–2 years	Reconstruct the node network; sign long-term agreements with regeneration plants	Total operating cost reduced by 9%–12%; lithium resource dependence reduced by 15%–20%	Full model + carbon-risk-cost collaborative optimization

Policy Adaptation Solution: Supporting Compliance with EU Carbon Policies. The model features a built-in compliance verification module, which is divided into two parts to address policy requirements such as the EU New Battery Regulation and CBAM.[22]: 1. Carbon Footprint Compliance: The system automatically calculates the full lifecycle carbon footprint of power batteries to ensure compliance with EU labeling requirements (e.g., reducing the carbon footprint of ID.4 batteries from 6.0 tons to 3.8 tons, meeting CBAM tariff exemption criteria). 2. Recycling Rate Compliance: When the recycling rate falls below 80%, the model automatically optimizes the layout of recycling centers and subsidy strategies.

5.3 Research Limitations and Future Directions

5.3.1 Limitations of the study

Data scope limitations: The empirical data focusing on a single European region and Volkswagen's single enterprise mainly comes from the European new energy vehicle supply chain (Volkswagen MEB platform), and does not cover major markets such as China and the United States, with two major limitations: First, regional differences impact: The supply chain structure differs between China and Europe, with China primarily using lithium iron phosphate batteries and Europe predominantly using ternary lithium batteries. The model's adaptability to non-European markets needs further validation. Second, differences in enterprise scale: Volkswagen is a leading automaker (with an annual production capacity exceeding 1 million units), while small and medium-sized automakers (with an annual production capacity <300,000 units) have lower supply chain complexity. The model may be "overly designed," requiring a simplified version for adaptation.

Model Assumption Limitations: To simplify the model complexity, two types of assumptions were made, which may deviate from reality and have two major limitations: First, the technical assumption: It does not consider the technological iteration of solid-state batteries (projected to account for 30% of the global new energy vehicle battery market by 2030, IEA, 2024), the recycling process of solid-state batteries, and the significant differences in carbon emission coefficients compared to ternary lithium batteries (solid-state battery production emits only 45kgCO_2/kWh, while recycling reduces emissions by 3.2kgCO_2/kWh); Second, the consumer behavior assumption: It assumes that recycling rates are only influenced by policies, ignoring consumer recycling willingness (e.g., European consumers have a recycling willingness of 75%, China 62%, EBA, 2024), and the actual recycling volume may be lower than the model's predicted value.

Limitations of the uncertainty framework: The model fails to account for extreme events and multi-source risk correlations. It only considers two types of disruptions—lithium supply chain and transportation chain—with the assumption of independent risks. Key omissions include: 1) Extreme events: Systemic risks like the 2022 European energy crisis that caused a 14-day shutdown of Volkswagen's Wolfsburg battery plant were not included. 2) Multi-source risk correlations: The model's assumption of independent risks may underestimate overall risks, as lithium and cobalt prices show a positive correlation (correlation coefficient 0.68, LME, 2024).

5.3.2 Future research direction

The research in this paper has made pioneering progress in theory, methodology, and other aspects, and can be further deepened and expanded in more directions in the future to promote the development of this field toward a more intelligent, robust, and strategically valuable direction. First, in terms of model applicability, three-dimensional expansion and the introduction of deeper models can be carried out. Spatially, in the future, regional customized models can be developed by collecting supply chain data from key regions such as China and the United States, adjusting model parameters. Technically, emerging technology routes such as solid-state batteries can be incorporated to construct a multi-technology hybrid supply chain dynamic optimization model. In terms of entities, the game behavior among suppliers, automakers, and recyclers can be considered, combining theories such as Stackelberg games with robust optimization to coordinate conflicts of interest among multiple entities and enhance the practical explanatory power of the model.

Secondly, breakthroughs in uncertainty management can be achieved through two dimensions: "extremes" and "correlations". For high-impact, low-probability extreme events like energy crises and geopolitical conflicts, Extreme Value Theory (EVT) and Generalized Pareto Distribution (GPD) can be employed to enhance model resilience. Simultaneously, Copula functions should be introduced to precisely characterize the complex correlation between price fluctuations of raw materials (e.g., lithium, cobalt) and logistics disruptions, enabling the construction of joint uncertainty sets for systematic and accurate assessment of supply chain risks. At the predictive model level, advanced architectures like Transformers can replace LSTM, leveraging their attention mechanisms to capture multi-year industrial cycle characteristics. On the data side, traditional structured data limitations should be overcome by integrating multimodal data sources such as satellite imagery (for production capacity monitoring) and social media sentiment (for political risk alerts), thereby building a "digital twin" system with more comprehensive and cutting-edge decision-making intelligence.

Finally, regarding policy adaptability, a long-term dynamic perspective must be established. The model's time horizon should extend from annual decisions to five-year or longer strategic cycles, dynamically incorporating progressive policy objectives such as the EU's 2030 target of 55% emission reduction and 2050 carbon neutrality, as well as long-term variables like rising carbon prices and technological iterations. Additionally, by considering global variations in carbon policies, it optimizes cross-border production and logistics layouts, providing long-term strategic decision-making support for enterprises to gain cost and compliance advantages under the new global green trade rules.

6. Conclusion

To address the triple challenges of carbon constraints, supply chain disruption risks, and cost pressures in the closed-loop supply chain of new energy vehicles, this study proposes an innovative methodology integrating long-term and short-term memory networks (LSTM) with robust optimization. Through theoretical modeling, algorithm design, and empirical analysis on the Volkswagen MEB platform, the following key conclusions are drawn:

At the methodological level, the developed "LSTM prediction-dynamic robust optimization" integrated framework effectively addresses the limitations of traditional OR methods. Compared to the conventional MIP model (Model-1), it achieves a 3.5% reduction in total operating costs, a 36.2% decrease in carbon emissions, and a 72.1% reduction in outage losses. When contrasted with the static robust model (Model-2), it demonstrates a 9.6% cost reduction, a 19.5% carbon emission reduction, and a 47.2% decrease in stockout rates, realizing a triple win in economic efficiency, environmental sustainability, and operational resilience.

Theoretical breakthrough: This study overcomes the theoretical bottleneck of OR multi-objective optimization under dynamic uncertainty by introducing a dynamic mapping mechanism termed "prediction error-uncertainty set radius", which achieves optimal balance between robustness and cost-effectiveness. Furthermore, it establishes a real-time closed-loop fusion paradigm integrating machine learning with OR, reducing decision-making latency from 72 hours to 24 hours, thereby providing a novel paradigm for OR to handle dynamic uncertainties.

In practical implementation: Building on the Volkswagen MEB platform pilot, we have established a phased roadmap for "short-term-medium-term-long-term" deployment. By 2025, this initiative is projected to reduce carbon costs by €12.8 million, cut supply chain disruption time by 40%, and increase recycling volume by 23%. The developed cost-benefit analysis template and policy adaptation module provide direct decision support for new energy vehicle manufacturers, helping them navigate EU carbon policies and supply chain risks.

The innovation of this study lies in its deep integration of machine learning's predictive capabilities with OR's optimization capabilities, providing a complete solution for closed-loop supply chain optimization in new energy vehicles—from theoretical models to practical tools. Future improvements could enhance the model's versatility and foresight through expanded data scope, refined uncertainty handling, and policy evolution, thereby contributing OR's wisdom to the sustainable development of the global new energy vehicle industry.

Reference

[1] European Commission. Regulation (EU) 2023/1542 on Batteries and Waste Batteries. Brussels: European Commission; 2024.
[2] European Commission. (2024). Carbon Border Adjustment Mechanism (CBAM) Implementation Guidelines 2026. Brussels: European Commission.
[3] Volkswagen Group. (2024). Sustainability Report 2024. Wolfsburg: Volkswagen AG.
[4] London Metal Exchange (LME). (2024). Battery Metals Price & Volatility Report 2024. London: LME.
[5] United States Geological Survey (USGS). (2024). Mineral Commodity Summaries 2024. Reston: USGS.
[6] International Energy Agency (IEA). (2024). Global EV Outlook 2024. Paris: IEA.
[7] Shen, L., Liu, Z., & Li, Y. (2023). Carbon-constrained closed-loop supply chain network design with uncertain demands and supply disruptions. European Journal of

Operational Research, 309(2), 678-692.

[8] Tu, S. (2025). Enlightenments from the Rise and Fall of the Red Sea: On the First Anniversary of the Red Sea Crisis. China Ports, (02), 20-22.

[9] Guide, V. D. R., Jayaraman, V., & Srivastava, R. (2003). Supply chain models for recycled materials. Management Science, 49(1), 102-117.

[10] Wang, H., Chen, J., & Zhang, H. (2022). Machine learning-aided demand forecasting for sustainable supply chains. European Journal of Operational Research, 298(3), 954-968.

[11] Liu, J. (2022). Order Decision and Contract Design Based on Distributionally Robust Optimization with Random Yield, Demand and Price (Doctoral Dissertation). South China University of Technology, Guangzhou.

[12] Salinas, D., Flunkert, V., & Gasthaus, J. (2019). DeepAR: Probabilistic forecasting with autoregressive recurrent networks. Advances in Neural Information Processing Systems, 32, 11387-11397.

[13] Zhou, Y., Li, Q., & Zhao, Y. (2025). Research on the Full-Life-Cycle Standard System of Power Batteries. China Standardization, (15), 102-105.

[14] Fang, S., Liu, Z., & Cheng, Y. (2025). Integration of Machine Learning Methods and Enterprise Management Research: Review and Prospect. Economic Management, 47(03), 183-208.

[15] Ling, Q. Y. (2025). Research on the Impact of the EU's New Battery Regulation on China's New Energy Vehicle Exports. In Proceedings of the Conference on New Quality Productive Forces and the Development of Emerging Economies (Volume 1) (pp. 374-383). Foshan University Press.

[16] European Energy Exchange (EEX). (2024). EU ETS Price Statistics 2024. Leipzig: EEX.

[17] Du, H. Y., & Dai, H. S. (2025). Patient Capital, Industrial Chain and Supply Chain Resilience, and High-Quality Development of Manufacturing Enterprises. Mathematics in Practice and Theory, 1-19.

[18] Yang, Y., Zang, Z., & Cheng, L. (2025). Robust Optimal Operation Strategy of Active Distribution Network Based on "Prediction-Control-Correction" Closed-Loop Feedback. Proceedings of the CSEE, 1-14.

[19] Xia, M. (2019). Research on Inventory Control Optimization of Closed-Loop Supply Chain with Uncertain Recovery Rate (Master's Dissertation). Nanjing University of Posts and Telecommunications, Nanjing.

[20] Fang, H. (2025). Seeking the "Pareto Optimal Solution" for the High-Quality Development of New Energy. People's Political Consultative Conference News, (005).

[21] Wu, J., & Wang, S. F. (2024). In-Depth Analysis of the EU's New Battery Regulation. Shanghai Auto, (07), 45-48+53.

