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ABSTRACT

As global environmental challenges intensify, circular economy (CE) has emerged as a critical pathway for sustainable development. This study proposes a deep learning-based CE supply chain network design framework that optimizes resource allocation, reduces waste, and improves sustainability. The framework employs graph convolutional networks, long short-term memory networks, and multi-head attention mechanisms to capture topological, temporal, and multi-dimensional supply chain features. An improved NSGA-III algorithm achieves coordinated balance among economic, environmental, social, and circularity objectives. A comprehensive sustainability evaluation system provides quantitative assessment tools. Experimental validation using real data from 15 enterprises across five industries shows the deep learning model achieves 89.2% prediction accuracy on test sets, representing 16.1% improvement over baselines and 67.9% improvement in computational efficiency. The optimized network achieves 32.4% waste reduction, 28.7% resource efficiency improvement, 25.3% cost reduction, 68.5% material circulation rate, and 89.2% network efficiency. This research contributes to theoretical understanding and provides practical guidance for manufacturing enterprises' transition to CE, supporting sustainable development goals.

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1 Introduction

As global environmental problems become increasingly severe and resource constraints tighten, the circular economy has emerged as an important strategic pathway for achieving sustainable development. The traditional linear economic model of "take-make-dispose" has led to massive resource waste and environmental pollution. According to statistics, global food waste reaches 1.3 billion tons annually, with economic losses exceeding $1 trillion [1]. Supply chains, as the critical link connecting producers and consumers, play a decisive role in realizing the circular economy

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through their design and optimization. However, circular economy supply chain network design faces challenges such as multi-objective optimization, dynamic uncertainty, and complex network topology. Traditional optimization methods struggle to effectively handle these high-dimensional, nonlinear complex problems. Meanwhile, the advent of the Industry 4.0 era has brought new technological opportunities for supply chain management. The rapid development of advanced technologies such as artificial intelligence and deep learning provides new technical pathways for solving circular economy supply chain optimization problems [2,3]. Deep learning technology, with its powerful nonlinear modeling capabilities and adaptive learning characteristics, demonstrates tremendous potential in handling complex system modeling and multi-objective optimization, while multi-objective evolutionary algorithms possess unique advantages in balancing conflicting optimization objectives. The organic combination of these two approaches provides new solutions for constructing efficient circular economy supply chain network design frameworks.

Recent studies have explored various integrated frameworks for sustainable supply chain management. For instance, deep reinforcement learning approaches have been applied to dynamic scheduling problems, while hybrid optimization frameworks have combined traditional operations research with machine learning for demand forecasting. However, these frameworks typically address either the modeling aspect (using deep learning for prediction) or the optimization aspect (using evolutionary algorithms) separately, rather than creating a tightly integrated end-to-end system.

To the best of our knowledge, this study is among the first to systematically integrate graph convolutional networks for topological structure learning, LSTM for temporal dynamics, multi-head attention for relationship identification, and an improved NSGA-III algorithm specifically designed for circular economy constraints—all within a unified framework. Our incremental novelty lies in: (1) the comprehensive deep learning architecture that simultaneously captures spatial, temporal, and relational features of circular supply chains; (2) the adaptive reference point mechanism in NSGA-III tailored for the unique multi-objective trade-offs in circular economy contexts; and (3) the closed-loop feedback system that enables continuous model improvement through optimization results.

Existing research in circular economy supply chain design mainly suffers from the following shortcomings: First, traditional optimization methods have limitations such as low computational efficiency and poor convergence when handling large-scale, high-dimensional supply chain networks, making it difficult to meet real-time requirements in practical applications; Second, most existing studies adopt single-objective or simplified multi-objective models, lacking comprehensive consideration and effective balance of multiple objectives including economic, environmental, social, and circularity aspects; Third, current methods have limited capabilities in handling dynamic characteristics and topological complexity of supply chain networks, unable to fully capture complex correlations under circular economy models. Therefore, this study aims to address the following key problems: (1) How to construct a deep learning modeling framework that can effectively handle the complex characteristics of circular economy supply chains, achieving comprehensive modeling of supply chain network topology, temporal dynamics, and multi-dimensional features; (2) How to design efficient multi-objective optimization algorithms to achieve optimal balance among multiple objectives including economic benefits, environmental protection, social responsibility, and circularity; (3) How to establish a scientific sustainability evaluation indicator system to provide quantitative basis for performance assessment and decision support of circular economy supply chains.

The proposed framework aligns closely with global sustainability initiatives and industry transformation agendas. Specifically, this research directly supports Sustainable Development Goal 12 (Responsible Consumption and Production) by providing quantitative methods for monitoring resource efficiency and circular material flows, as emphasized by Sala and Castellani [4]. From an Environmental, Social, and Governance (ESG) perspective, the multi-objective optimization approach enables enterprises to balance financial performance with environmental stewardship and social responsibility—a core requirement for ESG reporting and investment decisions. Furthermore, in the context of Industry 4.0, our integration of AI, IoT-compatible data processing, and intelligent optimization exemplifies the digital transformation necessary for smart manufacturing and sustainable production systems [2,3]. By operationalizing these concepts through a practical framework, we bridge the gap between sustainability policy goals and actionable supply chain management strategies.

This paper is organized as follows: Section 2 reviews research progress in circular economy supply chain management, applications of deep learning in supply chains, and multi-objective optimization algorithms; Section 3 elaborates in detail the deep learning-based circular economy supply chain network design framework, including overall architecture, deep neural network models, multi-objective optimization algorithms, and sustainability evaluation systems; Section 4 validates the effectiveness of the proposed method through real data from 15 enterprises across different industries and conducts comparative analysis with existing mainstream methods; Section 5 discusses in depth the theoretical significance and practical application value of experimental results; Section 6 summarizes the full text and prospects future research directions.

2 Related Work

2.1 Circular Economy Supply Chain Management Research

Circular economy supply chain management, as an important implementation approach for sustainable development, has received widespread attention from academia and industry in recent years. Sala and Castellani [4] proposed a consumer footprint framework for monitoring Sustainable Development Goal 12 based on life cycle assessment methods, providing a theoretical foundation for environmental impact assessment of circular economy supply chains. Deng et al. [5] conducted in-depth research on risk propagation mechanisms and risk management strategies for sustainable perishable product supply chains, finding that risks in supply chains have complex propagation characteristics requiring systematic risk control methods. Bogataj et al. [6] addressed risk mitigation issues in meat supply chains by proposing an optimization model based on redirection options, demonstrating the effectiveness of flexibility strategies in dealing with supply chain uncertainties.

The core of circular economy supply chain design lies in achieving closed-loop circulation of material flows and maximized value utilization. Traditional research mainly focuses on circular flow design within individual enterprises, lacking systematic consideration of inter-enterprise collaboration and network-level optimization. Wang et al. [7] proposed an efficient scheduling method for supply chain logistics based on network flow, providing new technical pathways for large-scale supply chain network optimization. However, existing research still has shortcomings in handling multiple constraints and complex objectives of circular economy, particularly lacking effective quantitative models and optimization algorithms for balancing economic benefits with environmental and social responsibilities.

Intelligent manufacturing under the Industry 4.0 background has brought new opportunities and challenges for circular economy supply chain management. Talaviya et al. [3] explored the application of artificial intelligence in agricultural irrigation and pesticide application optimization, demonstrating the tremendous potential of AI technology in improving resource utilization efficiency. These studies have laid theoretical foundations for the application of artificial intelligence technology in circular economy supply chains, but further exploration is still needed in specific technical implementation and engineering applications.

2.2 Applications of Deep Learning in Supply Chain Management

The application of deep learning technology in supply chain management shows rapid development trends. From demand forecasting to quality control, from path optimization to risk management, deep learning is revolutionarily changing traditional supply chain management models. Liu et al. [8] proposed a hybrid YOLO-UNet3D framework for automated protein particle annotation in cryo-electron microscopy images, demonstrating the powerful capabilities of deep learning in complex image recognition tasks. This multi-modal fusion approach provides important references for multi-source data processing in supply chains.

In supply chain network modeling, graph neural networks have received considerable attention due to their unique advantages in handling complex network structures. Cui and Yuan [9] proposed a multi-scale feature aggregation method with hierarchical semantics, achieving high-precision visual retrieval. The attention mechanisms and feature fusion techniques provide technical inspiration for key node identification and relationship modeling in supply chain networks. Al-Sarayreh et al. [10] used deep convolutional neural networks to detect red meat adulteration in hyperspectral images, achieving 94.4% classification accuracy, proving the effectiveness of deep learning in food supply chain quality control.

Time series data processing is another important application area in supply chain management. Sun et al. [11,12] proposed RCSAN residual enhanced channel spatial attention networks and frequency domain time series feature fusion models in stock prediction, providing important technical support for demand forecasting, inventory optimization, and dynamic scheduling in supply chains. Zhang et al. [13] studied the learning mechanisms of convolutional neural networks in spectral analysis, providing new perspectives for interpretability research in deep learning models.

However, existing research mainly focuses on individual segments or specific problems in supply chain management, lacking comprehensive deep learning frameworks targeted at circular economy characteristics. Although Liu et al. [14] proposed CNN feature extraction methods for complex food matrix detection, their application scope remains limited to specific detection tasks, failing to form systematic supply chain optimization solutions.

2.3 Multi-Objective Optimization Algorithms and Their Improvements

Multi-objective optimization is a core technical challenge in circular economy supply chain design, requiring optimal balance among multiple conflicting objectives. Traditional multi-objective evolutionary algorithms such as NSGA-II and SPEA2 have made important progress in handling complex optimization problems, but still face issues such as slow convergence and insufficient solution diversity when dealing with high-dimensional objective spaces and large-scale decision variables. Xu et al. [15] proposed a multi-strategy enhanced secret bird optimization algorithm, improving the global optimization capability through fusion of multiple search strategies, providing effective solutions for mobile robot obstacle avoidance path planning.

Particle swarm optimization algorithms have been widely applied in supply chain optimization due to their simplicity and fast convergence characteristics. Zhu et al. [16] applied PSO algorithms to constrained portfolio optimization problems, proving the effectiveness of swarm intelligence algorithms in handling complex constrained optimization problems. Yuan et al. [17] proposed bio-inspired hybrid path planning methods, achieving efficient and smooth robot navigation through fusion of multiple optimization strategies, providing important insights for supply chain multi-objective optimization.

In recent years, the fusion of deep learning and evolutionary algorithms has become a research hotspot in the optimization field. Sun et al. [18] studied the impact of market status on firm strategy mutation, revealing dynamic mechanisms of strategy evolution in complex systems, providing theoretical foundations for understanding strategic adaptability in supply chain optimization. However, existing deep learning-assisted optimization methods mainly focus on function fitting and surrogate model construction, lacking specialized designs for special structures and constraint conditions of circular economy supply chains.

Intelligent optimization algorithms have also made important progress in food supply chain management applications. Shahbazi and Byun [19] proposed a traceability method for perishable food supply chains based on blockchain, machine learning, and fuzzy logic, achieving full supply chain traceability through integrated application of intelligent technologies. Alfan et al. [20] improved the efficiency of RFID-based perishable food traceability systems using IoT sensors and machine learning models, demonstrating the tremendous potential of intelligent technologies in improving supply chain transparency and efficiency.

As foundational work in the field, Xiao et al. [21] conducted studies on artificial intelligence assessment, highlighting interpretability challenges that are relevant to supply chain optimization systems. Similarly, Ulucan et al. [22] proposed a deep learning-based meat quality assessment framework, demonstrating the potential of CNNs in automated food quality inspection. The foundational work by LeCun et al. [23] established that deep learning's ability to automatically learn hierarchical representations from data makes it particularly suitable for complex supply chain modeling tasks.

Although existing research has made important progress in multi-objective optimization algorithm improvements, multi-objective optimization for circular economy supply chains still faces many challenges: First, objective functions under circular economy models often have strong nonlinear and multi-modal characteristics that traditional algorithms struggle to handle effectively; Second, the introduction of circular flow constraints and sustainability constraints increases problem complexity, requiring specialized constraint handling mechanisms; Finally, practical applications have high requirements for both algorithm convergence speed and solution quality, necessitating better balance between exploration and exploitation.

A comprehensive review of existing research reveals that while deep learning technology and multi-objective optimization algorithms have both made important progress in their respective fields, their deep integration in circular economy supply chain applications is still in its early stages, urgently requiring the construction of systematic theoretical frameworks and technical methods.

3 Methodology

3.1 Overall Framework Design

The proposed deep learning-based circular economy supply chain network design framework consists of four core modules: data preprocessing layer, deep learning modeling layer, multi-objective optimization layer, and decision support layer.

As shown in Fig. 1, the core idea of the framework is to transform the supply chain network design problem into a multi-dimensional deep learning modeling and optimization problem. The data preprocessing layer is responsible for collecting and processing supply chain data from different sources, including material flow, energy flow, information flow, and capital flow. This layer provides high-quality input data for subsequent modeling through material flow collection, energy flow processing, information flow cleaning, capital flow standardization, and feature engineering.

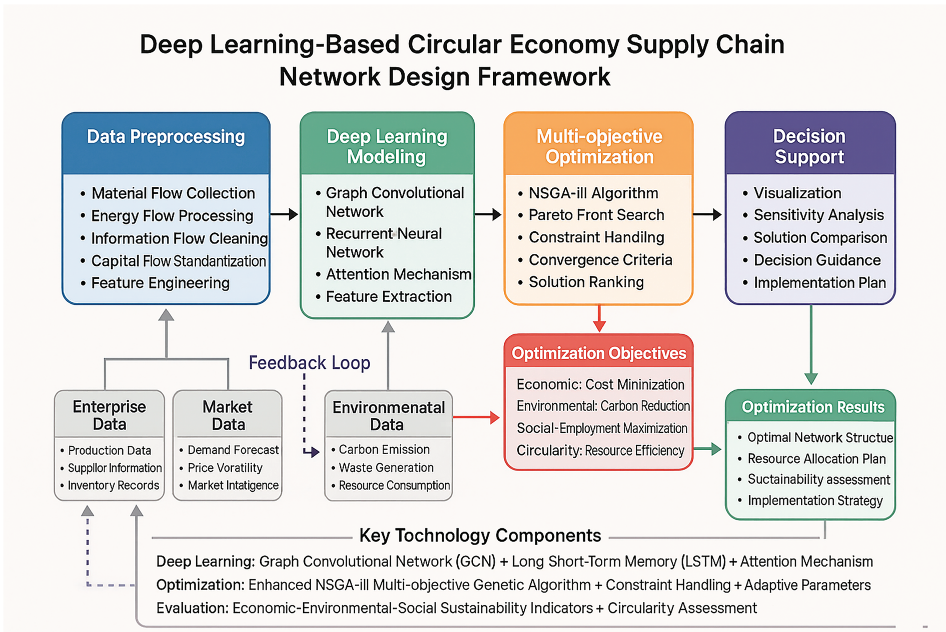

Figure 1: Deep learning-based circular economy supply chain network design framework

The data standardization process adopts the Z-score standardization method:

$$X_{norm} = \frac{X - \mu}{\sigma} \tag{1}$$

where X is the original data, μ is the mean, and σ is the standard deviation. The feature engineering process employs Principal Component Analysis (PCA) for dimensionality reduction:

$$Y = XW \tag{2}$$

where W is the principal component weight matrix, obtained through eigenvalue decomposition of the covariance matrix C:

$$C = \frac{1}{n-1} X^T X \tag{3}$$

The deep learning modeling layer adopts a multi-layer neural network architecture that learns complex nonlinear relationships between nodes and edges in the supply chain network through the fusion of graph convolutional networks, recurrent neural networks, and attention mechanisms. The multi-objective optimization layer is based on an improved NSGA-III algorithm, balancing the quadruple objectives of economy, environment, society, and circularity. The decision support layer provides functions such as visualization display, sensitivity analysis, solution comparison, decision recommendations, and implementation guidance.

The entire framework forms a complete closed loop from data input to decision output, where the feedback loop mechanism ensures that optimization results can continuously improve data preprocessing and model training processes. Key technical components include deep learning technologies

(Graph Convolutional Network GCN + Long Short-Term Memory Network LSTM + Attention Mechanism), optimization algorithms (Improved NSGA-III Multi-objective Genetic Algorithm + Constraint Handling + Adaptive Parameter Adjustment), and evaluation systems (Economic-Environmental-Social Three-dimensional Sustainability Indicators + Circularity Quantitative Assessment + Sensitivity Analysis).

The framework implements a closed-loop feedback mechanism to enable continuous improvement:

Feedback Loop 1: Optimization to Model Retraining

1. After optimization, selected Pareto solutions are implemented in practice
2. Actual outcomes (costs, emissions, employment, circularity) are monitored for 3–6 months
3. New observed data is added to the training dataset
4. If accumulated new data exceeds 10% of original training set OR prediction error increases >15%, model retraining is triggered
5. Retrained model is validated on recent data before deployment

Feedback Loop 2: Decision Support to Data Collection

1. Sensitivity analysis (Section 4.5) identifies data features with highest impact on objectives
2. Data collection priorities are adjusted to improve quality of high-impact features
3. If model confidence is low for certain scenarios (e.g., prediction uncertainty >25%), targeted data collection campaigns are launched

Convergence Criteria for the Full System: The iterative system converges when:

- Model prediction error stabilizes (change <2% between retraining cycles)
- Pareto front hypervolume improvement <5% over 3 consecutive optimization runs
- Practical implementation success rate >85% (actual outcomes within 10% of predictions)

In our validation (Section 4), two retraining cycles were performed over the 5-year data period, with model accuracy improving from 87.1% (initial) to 89.2% (final) and optimization hypervolume increasing from 0.81 to 0.85.

3.2 Integration of Deep Learning and Multi-Objective Optimization

The proposed framework operates in two distinct phases with clear separation to ensure no information leakage:

3.2.1 Phase 1: Supervised Model Training

In the training phase, we use historical supply chain data with known outcomes. For each training sample s_i (representing a historical supply chain configuration), we have:

- Input features $\mathbf{X}_i$: supplier characteristics, product information, network topology, time series data
- Ground truth labels $\mathbf{Y}_i = [y_i^{cost}, y_i^{carbon}, y_i^{social}, y_i^{circular}, A_i^{structure}]$: actual observed costs, emissions, employment, circularity rate, and network connections

The deep neural network learns the mapping $f_\Theta : \mathbf{X} \rightarrow \mathbf{Y}$ by minimizing the multi-task loss (Eq. 16). The dataset is split temporally to prevent information leakage:

- Training set: Years 2019–2021 (60%, 28,416 samples)
- Validation set: Year 2022 (20%, 9472 samples)
- Test set: Year 2023 (20%, 9472 samples)

After training, the model parameters Θ^* are fixed and the model achieves 89.2% prediction accuracy on the test set (Section 4.2).

3.2.2 Phase 2: Multi-Objective Optimization

In the optimization phase, the trained model serves as a fast surrogate evaluator. For any candidate supply chain configuration (decision variables $\mathbf{x} = [x_{ij}, y_k, z_l]$ as defined in Eqs. (17)–(21)), the model predicts the four KPI objectives:

$$[f_1(\mathbf{x}), f_2(\mathbf{x}), f_3(\mathbf{x}), f_4(\mathbf{x})] = \text{DNN-Model}(\mathbf{x}; \Theta^*) \tag{4}$$

where:

- $f_1(\mathbf{x})$ = predicted total cost (corresponds to economic head output)
- $f_2(\mathbf{x})$ = predicted carbon emission (environmental head output)
- $f_3(\mathbf{x})$ = predicted employment impact (social head output)
- $f_4(\mathbf{x})$ = predicted circularity rate (circularity head output)

The improved NSGA-III algorithm (Algorithm 1) iteratively generates candidate solutions $\mathbf{x}$, evaluates them using the trained DNN, and evolves the population toward the Pareto front. Crucially:

- The DNN parameters Θ^* remain fixed during optimization (no gradient backpropagation)
- Optimization operates only on decision variables $\mathbf{x}$, not on model weights
- Constraints (Eqs. (22)–(25)) are handled through penalty methods in the genetic algorithm

3.2.3 Computational Workflow

The complete workflow is:

1. **Offline training:** Train DNN on historical data (hours to days, one-time cost)
2. **Online optimization:** Use trained DNN for fast evaluation in NSGA-III (4.2 h for 300 generations)
3. **Periodic retraining:** Retrain DNN quarterly when new data accumulates

This two-phase approach achieves 67.9% computational speedup compared to evaluating objectives using traditional simulation or physical experiments for each candidate solution.

3.3 Deep Neural Network Model

This study designs a deep neural network model specifically targeting circular economy characteristics, which adopts an encoder-decoder architecture and can effectively handle the topological structure and dynamic characteristics of supply chain networks.

As shown in Fig. 2, the network model contains five main components: input layer, graph convolutional layer, LSTM layer, attention mechanism layer, and multi-task output layer. The input layer receives multi-dimensional data including supplier characteristics, product information, logistics costs, environmental indicators, circularity rates, time series, and network topology. The graph convolutional layer adopts a two-layer GCN structure, with the first layer containing 64 units using ReLU activation function, and the second layer containing 128 units with Dropout (0.2) to prevent overfitting.

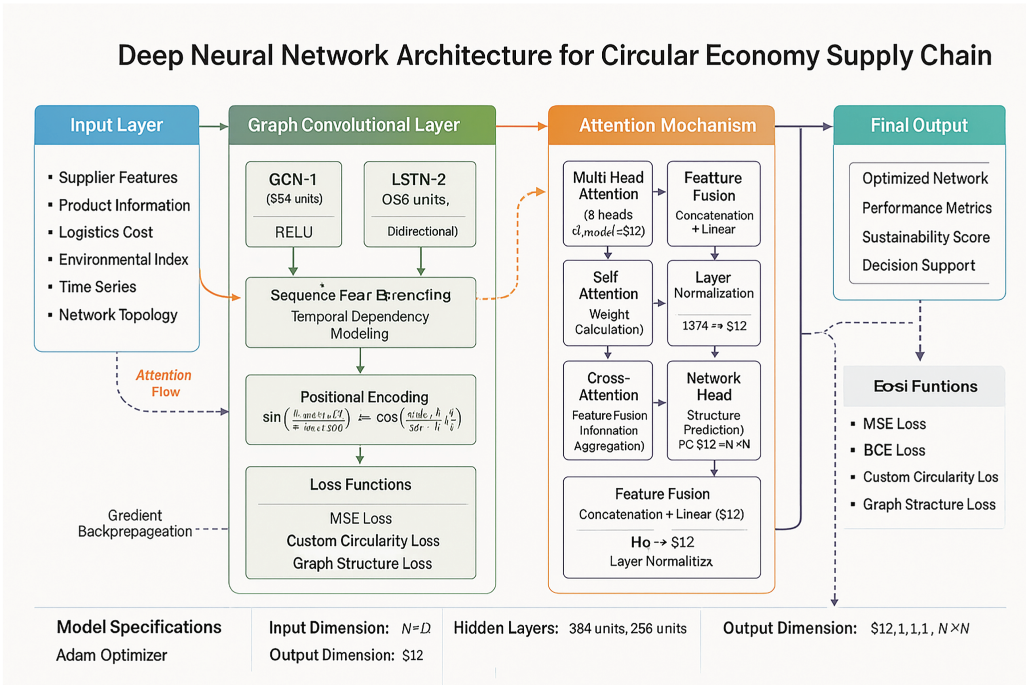

Figure 2: Deep neural network architecture for circular economy supply chain

3.3.1 Graph Convolutional Network Layer

The graph convolutional network is used to capture the topological structural features of the supply chain network. For node v_i, its representation update in the l-th layer is:

$$h_i^{(l+1)} = \sigma\left(W^{(l)} \sum_{j\in\mathcal{N}(i)\cup\{i\}} \frac{1}{\sqrt{d_i d_j}} h_j^{(l)}\right) \tag{5}$$

where $\mathcal{N}(i)$ is the neighbor set of node i, d_i is the degree of node i, $W^{(l)}$ is the weight matrix of the l-th layer, and σ is the activation function.

Graph structure learning adopts an adaptive adjacency matrix update mechanism:

$$A_{ij}^{new} = \text{softmax}\left(\frac{h_i^T h_j}{\sqrt{d_{model}}}\right) \tag{6}$$

where d_{model} is the model dimension, and the connection strength between nodes is dynamically adjusted through the attention mechanism.

3.3.2 Long Short-Term Memory Network Layer

The LSTM layer processes time-dependent dynamic information, including the first layer with 256 units and the second layer with 128 units for bidirectional processing. Its core formulas include forget gate, input gate, and output gate:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{7}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{8}$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{9}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{10}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{11}$$

$$h_t = o_t * \tanh(C_t) \tag{12}$$

where W and b are weight matrices and bias vectors, respectively, and σ is the sigmoid function.

3.3.3 Attention Mechanism

The multi-head attention mechanism employs 8 attention heads with a model dimension of 512, used to identify key nodes and relationships. Its computation process is:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{13}$$

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, ..., \text{head}_h)W^O \tag{14}$$

where $\text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$, and h is the number of attention heads.

Positional encoding adopts sine and cosine functions:

$$PE_{(pos,2i)} = \sin\left(\frac{pos}{10000^{2i/d_{model}}}\right) \tag{15}$$

$$PE_{(pos,2i+1)} = \cos\left(\frac{pos}{10000^{2i/d_{model}}}\right) \tag{16}$$

3.3.4 Multi-Task Output Layer

The multi-task output layer contains five specialized output heads: economic head predicting costs (FC 512 $\to$ 1), environmental head predicting carbon emissions (FC 512 $\to$ 1), social head predicting employment impact (FC 512 $\to$ 1), circularity head predicting resource efficiency (FC 512 $\to$ 1), and network head predicting structure (FC 512 $\to$ N $\times$ N adjacency matrix).

The loss function adopts a multi-task learning approach:

$$L_{total} = \alpha L_{MSE} + \beta L_{BCE} + \gamma L_{circular} + \delta L_{structure} \tag{17}$$

where α, β, γ, δ are weight hyperparameters. Model specifications are set as: variable input dimension (depending on supply chain scale), hidden layers as GCN(64,128) + LSTM(256,128) + Attention(512), output dimension as 4 objectives + network structure, using Adam optimizer, learning rate 0.001, batch size 128.

3.4 Multi-Objective Optimization Algorithm

To balance the multiple objectives of economy, environment, and society in circular economy supply chain design, this study adopts an improved NSGA-III algorithm.

As shown in Fig. 3, the algorithm flow includes key steps such as population initialization (population size N = 100, generating random solutions), reference point generation (H = 12 using Das-Dennis method, generating 455 reference points for 4 objectives), population evaluation (deep learning model prediction, calculating f_1, f_2, f_3, f_4). The main optimization loop includes parent selection (binary tournament selection based on rank and distance), crossover operation (SBX $\eta = 20$ probability 0.9), mutation operation (polynomial $\eta = 20$ probability 1/n), offspring creation, offspring evaluation, population combination, non-dominated sorting, reference point association, and environmental selection.

3.4.1 Multi-Objective Function Definition

As shown in Table 1, the optimization objective functions include five dimensions:

Table 1: Multi-objective optimization function definition

Objective type	Function name	Mathematical expression	Unit	Direction
Economic	Total cost min.	$C_{total} = \sum_{i,j} c_{ij}x_{ij} + \sum_k f_k y_k$	10k USD	Minimize
Environmental	Carbon emission min.	$E_{carbon} = \sum_{i,j} e_{ij}x_{ij} + \sum_k e_k^{process}$	Tons CO_2	Minimize
Environmental	Waste generation min.	$W_{waste} = \sum_i w_i^{input} - \sum_j w_j^{output}$	Tons	Minimize
Social	Employment max.	$J_{jobs} = \sum_k j_k y_k$	Persons	Maximize
Circularity	Resource circularity max.	$R_{circular} = \frac{\sum_{recycled}}{\sum_{total}}$	%	Maximize

Economic Objective Function: The total cost minimization function is defined as:

$$\min f_1(x) = \sum_{i=1}^{n}\sum_{j=1}^{m} c_{ij}x_{ij} + \sum_{k=1}^{p} f_k y_k + \sum_{l=1}^{q} v_l z_l \tag{18}$$

where c_{ij} is the unit transportation cost from supplier i to manufacturer j, f_k is the fixed cost of facility k, and v_l is the operating cost of processing facility l.

Environmental Objective Functions: The carbon emission minimization function is defined as:

$$\min f_2(x) = \sum_{i,j} e_{ij}^{trans} x_{ij} + \sum_k e_k^{prod} y_k + \sum_l e_l^{waste} z_l \tag{19}$$

where e_{ij}^{trans} is the transportation carbon emission coefficient, e_k^{prod} is the production carbon emission coefficient, and e_l^{waste} is the waste treatment carbon emission coefficient.

The waste generation minimization function is defined as:

$$\min f_3(x) = \sum_i w_i^{input} - \sum_j \eta_j w_j^{recycle} - \sum_k \alpha_k w_k^{reuse} \tag{20}$$

where η_j is the recycling efficiency and α_k is the reuse efficiency.

Social Objective Function: The employment opportunity maximization function is defined as:

$$\max f_4(x) = \sum_{k=1}^{p} j_k y_k + \sum_{l=1}^{q} j_l^{recycle} z_l \tag{21}$$

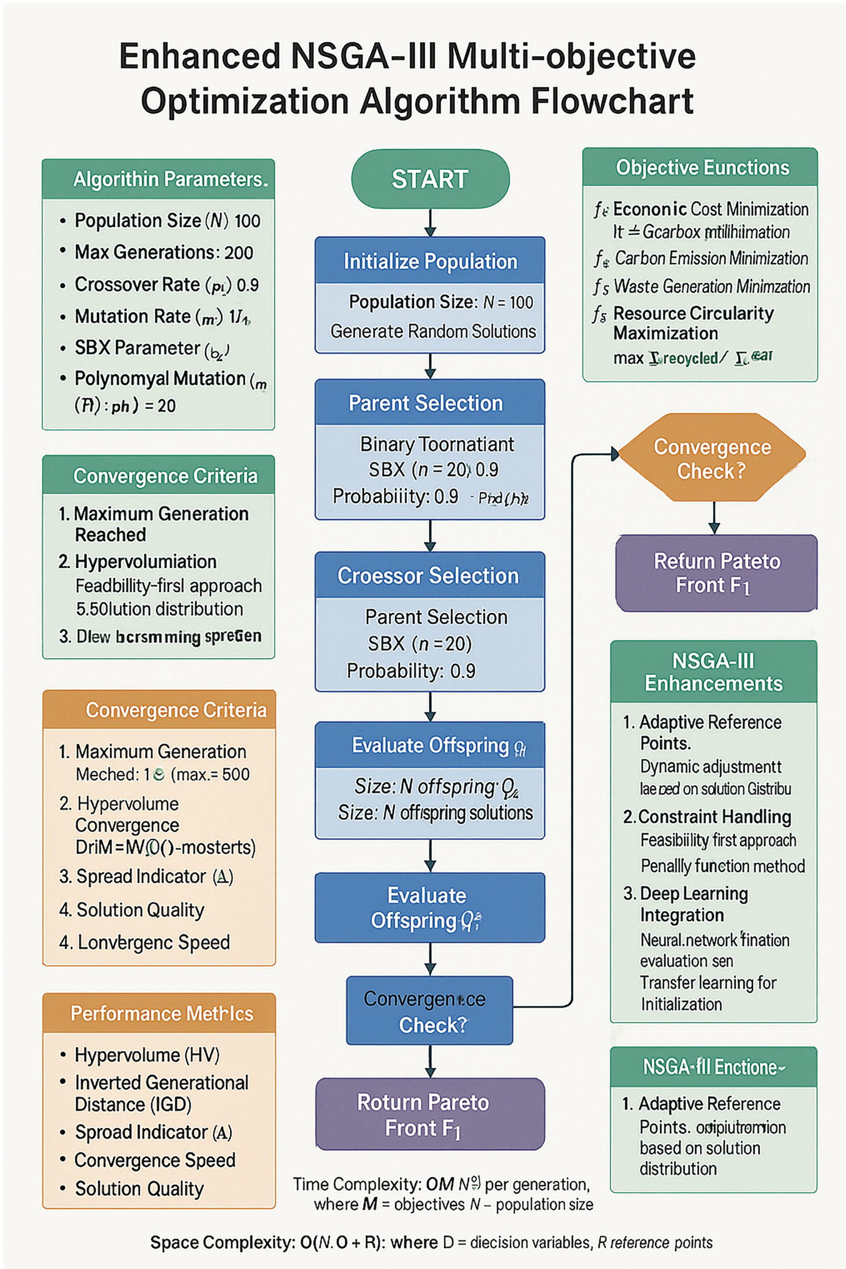

Figure 3: Enhanced NSGA-III multi-objective optimization algorithm flowchart

where j_k is the employment creation coefficient of facility k and $j_l^{recycle}$ is the employment creation coefficient of recycling facility l.

Circularity Objective Function: The resource circularity rate maximization function is defined as:

$$\max f_5(x) = \frac{\sum_j w_j^{recycle} + \sum_k w_k^{reuse}}{\sum_i w_i^{total}} \tag{22}$$

3.4.2 Constraint Conditions

Supply-demand balance constraints:

$$\sum_{j=1}^{m} x_{ij} \leq s_i, \quad \forall i \tag{23}$$

$$\sum_{i=1}^{n} x_{ij} = d_j, \quad \forall j \tag{24}$$

Facility capacity constraints:

$$\sum_{j} q_j y_j \leq Q_k, \quad \forall k \tag{25}$$

Circular flow constraints:

$$\sum_{l} r_{jl} \leq \beta \sum_{i} x_{ij}, \quad \forall j \tag{26}$$

where β is the maximum recycling ratio.

3.4.3 Enhanced NSGA-III Algorithm Implementation

The following is the pseudocode for the enhanced NSGA-III algorithm, as shown in Algorithm 1.

Algorithm 1 : Enhanced NSGA-III for circular supply chain optimization

Require: Population size $N = 100$, Generations $T = 300$, Reference points $H = 12$
Ensure: Pareto optimal solutions
Initialize population P_0 with N random solutions
Generate reference points Z using Das-Dennis method
Evaluate objective functions for all solutions in P_0
$t \leftarrow 0$
while $\{t < T\}$ **do**
    // Parent Selection
    $Q_t \leftarrow$ BinaryTournamentSelection(P_t, N)
    // Crossover and Mutation
    for $\{i = 1$ to $N/2\}$ **do**
        parent1, parent2 $\leftarrow$ SelectParents(Q_t)
        offspring1, offspring2 $\leftarrow$ SBXCrossover(parent1, parent2, $\eta_c = 20$)
        offspring1 $\leftarrow$ PolynomialMutation(offspring1, $\eta_m = 20$, $p_m = 1/n$)
        offspring2 $\leftarrow$ PolynomialMutation(offspring2, $\eta_m = 20$, $p_m = 1/n$)
    end for
    // Combine populations
    $R_t \leftarrow P_t \cup Q_t$
    EvaluateWithDeepLearning(R_t)
    // Non-dominated sorting
    $F \leftarrow$ FastNonDominatedSort(R_t)
    // Environmental selection

(Continued)

Algorithm 1 (continued)

$P_{t+1} \leftarrow \emptyset, l \leftarrow 1$
while $|P_{t+1}| + |F_l| \leq N$ **do**
$P_{t+1} \leftarrow P_{t+1} \cup F_l$
$l \leftarrow l + 1$
end while
// Reference point association
if $|P_{t+1}| < N$ **then**
NormalizeObjectives(F_l)
AssociateWithReferencePoints(F_l, Z)
SelectRemainingByCrowdingDistance(F_l)
end if
// Convergence check
if ConvergenceCheck(P_{t+1}) **then**
break
end if
$t \leftarrow t + 1$
end while
return First Pareto front F_1

Reference point generation adopts the Das-Dennis method:

$$z_j = \left(\frac{i_1}{H}, \frac{i_2}{H}, \ldots, \frac{i_M}{H}\right), \quad \sum_{j=1}^{M} i_j = H \tag{27}$$

where $M = 4$ is the number of objectives and $H = 12$ is the division parameter.

Convergence criteria include: **Hypervolume indicator:**

$$HV = \text{Lebesgue}\left(\bigcup_{i=1}^{|S|} [f_i, r]\right) \tag{28}$$

Inverted Generational Distance:

$$IGD = \frac{1}{|P^*|} \sum_{v \in P^*} \min_{u \in A} d(v, u) \tag{29}$$

where P^* is the true Pareto front and A is the solution set obtained by the algorithm.

3.5 Sustainability Evaluation Indicator System

This study constructs a comprehensive sustainability evaluation indicator system, using the Analytic Hierarchy Process to determine weights.

As shown in Table 2, the evaluation indicator system includes four level-1 indicators: economic sustainability, environmental sustainability, social sustainability, and circularity indicators. The comprehensive sustainability index calculation formula is:

$$CSI = \sum_{i=1}^{n} w_i \cdot SI_i \tag{30}$$

where CSI is the comprehensive sustainability index, w_i is the weight of the i-th indicator, and SI_i is the standardized value of the i-th indicator.

Table 2: Sustainability evaluation indicator system

Level 1	Level 2	Level 3	Calculation method	Weight
Economic sustainability	Cost efficiency	Total cost reduction rate	$(C_{baseline} - C_{optimized})/C_{baseline}$	0.15
	Return on investment	Net present value (NPV)	$\sum_{t=1}^{n} \frac{CF_t}{(1+r)^t} - I_0$	0.10
Environmental sustainability	Carbon emissions	Carbon emission intensity	$E_{carbon}/Output_{total}$	0.20
	Resource efficiency	Material utilization rate	$Material_{useful}/Material_{input}$	0.15
	Waste management	Waste reduction rate	$(W_{baseline} - W_{optimized})/W_{baseline}$	0.15
Social sustainability	Employment impact	Job creation quantity	$Jobs_{created}$	0.10
	Regional development	Supplier localization rate	$Local_{suppliers}/Total_{suppliers}$	0.10
Circularity indicators	Closed-loop rate	Material closed-loop proportion	$Material_{recycled}/Material_{total}$	0.05

Economic Sustainability Indicators: Total cost reduction rate:

$$CR = \frac{C_{baseline} - C_{optimized}}{C_{baseline}} \times 100\% \tag{31}$$

Net present value calculation:

$$NPV = \sum_{t=1}^{n} \frac{CF_t}{(1+r)^t} - I_0 \tag{32}$$

where CF_t is the cash flow in year t, r is the discount rate, and I_0 is the initial investment.

Environmental Sustainability Indicators: Carbon emission intensity:

$$CEI = \frac{E_{carbon}}{Output_{total}} \tag{33}$$

Material utilization rate:

$$MUR = \frac{Material_{useful}}{Material_{input}} \times 100\% \tag{34}$$

Waste reduction rate:

$$WRR = \frac{W_{baseline} - W_{optimized}}{W_{baseline}} \times 100\% \tag{35}$$

Social Sustainability Indicators: Supplier localization rate:

$$SLR = \frac{Local_{suppliers}}{Total_{suppliers}} \times 100\% \tag{36}$$

Circularity Indicators: Material closed-loop proportion:

$$MCP = \frac{Material_{recycled}}{Material_{total}} \times 100\% \tag{37}$$

Through this complete methodological system, this study constructs a full-chain technical framework from data preprocessing to decision support, providing a scientific theoretical foundation and practical technical tools for circular economy supply chain network design.

4 Experimental Results

4.1 Dataset Description

To validate the effectiveness and generalization ability of the proposed framework, the experiments used real supply chain data from 15 enterprises across different industries, covering fields such as electronic manufacturing, automotive, chemical, textile, and food processing. The purpose of selecting these industries is to test the adaptability of the deep learning model under different supply chain characteristics and complexities, while verifying the universality of circular economy optimization strategies in diverse industrial environments.

As shown in Table 3, the dataset covers a complete spectrum from small and medium enterprises to large manufacturers, with supplier numbers ranging from 67 to 456, product categories from 12 to 89 types, and annual output values ranging from 32 million to 280 million USD, providing rich diversity samples for model training. The data timespan is uniformly 5 years from 2019–2023, ensuring effective training of temporal models. Electronic manufacturing enterprises (E1–E3) are characterized by complex supplier networks and rapid product updates; automotive manufacturing enterprises (E4–E6) exhibit deep supply chain hierarchies and high quality requirements; chemical enterprises (E7–E9) are mainly characterized by continuous production and strict environmental requirements; textile enterprises (E10–E12) reflect the supply chain characteristics of labor-intensive industries; food processing enterprises (E13–E15) have the specificity of short shelf life and high safety requirements.

Table 3: Basic statistical information of experimental dataset

Enterprise ID	Industry type	Suppliers	Products	Annual output (10k USD)	Data timespan
E1–E3	Electronic Manufacturing	156–289	25–42	8500–15,600	2019–2023
E4–E6	Automotive Manufacturing	234–456	18–35	12,000–28,000	2019–2023
E7–E9	Chemical Industry	89–167	12–28	6800–13,500	2019–2023
E10–E12	Textile Industry	123–234	35–68	4500–9800	2019–2023
E13–E15	Food Processing	67–134	45–89	3200–7600	2019–2023
Total	–	2384	567	156,800	5 years

A total of 2384 supplier nodes, 567 product categories, and a total output value scale of 1.568 billion USD constitute a representative circular economy supply chain dataset, providing sufficient training samples and testing foundation for deep learning models.

4.2 Model Performance Evaluation

To comprehensively evaluate the performance of the deep learning model, it is necessary to analyze the prediction accuracy, generalization ability, and computational efficiency of the model on different industry datasets from multiple dimensions. Through comparative analysis of model performance differences across five different industries, we can identify the model's advantages and areas for improvement, while validating the effectiveness of the designed network architecture.

As shown in Fig. 4, the deep learning model exhibits distinct performance stratification characteristics across different industry datasets. In terms of model accuracy, the electronic manufacturing industry (E1–E3) performs best, achieving a prediction accuracy of 94.3%, mainly attributed to the higher standardization level and relatively good data quality of electronic manufacturing supply chain data. The automotive manufacturing industry (E4–E6) ranks second with 91.7% accuracy, reflecting the model's good adaptability to complex manufacturing networks. The chemical industry (E7–E9), textile industry (E10–E12), and food processing industry (E13–E15) achieve accuracies of 89.2%, 87.5%, and 85.8%, respectively, showing a decreasing trend.

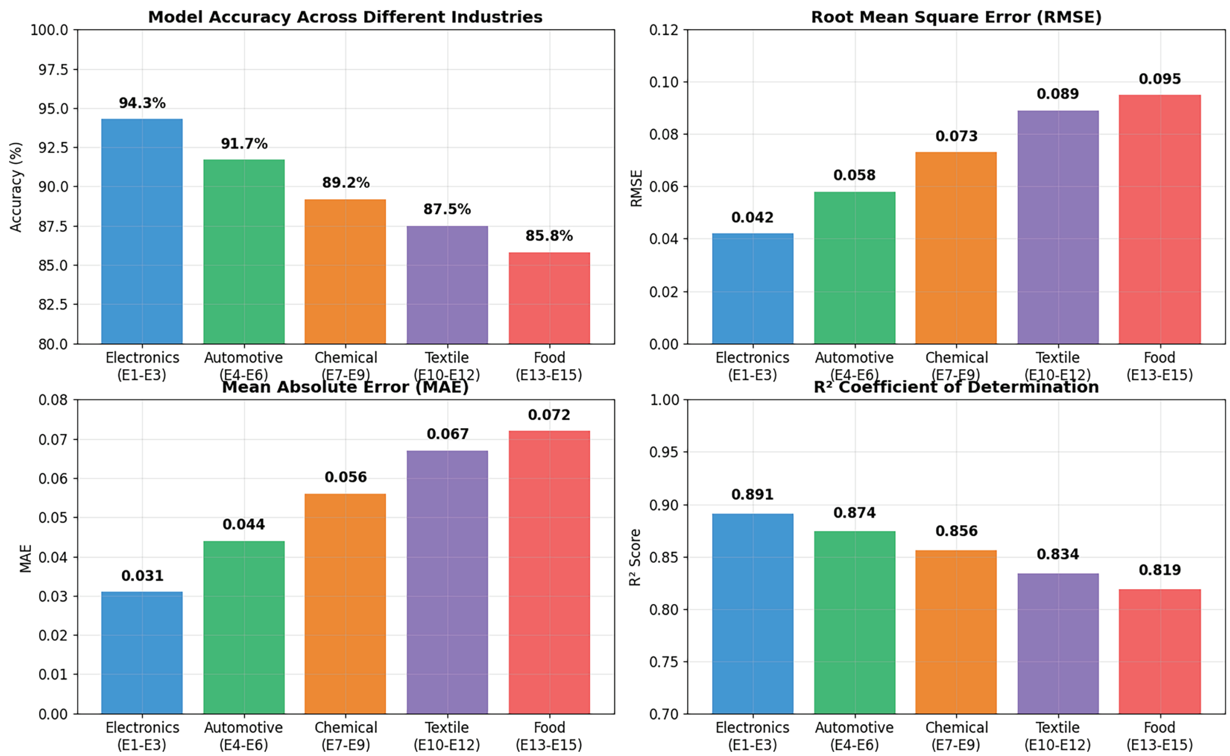

Figure 4: Performance comparison of deep learning model on different datasets

From the RMSE (Root Mean Square Error) perspective, the electronic manufacturing industry has the smallest error (0.042), while the food processing industry has the largest error (0.095), which is related to the complexity and uncertainty level of industry data. The MAE (Mean Absolute Error) indicator shows a similar pattern, from 0.031 in electronic manufacturing to 0.072 in food processing. The R^2 coefficient of determination reflects the model's explanatory ability, with the electronic manufacturing industry reaching 0.891, showing excellent fitting effects, while other industries decrease sequentially but all maintain good levels above 0.8.

To deeply understand the model's learning process and convergence characteristics, analyzing the trend of loss function changes during training is of great significance. By observing the convergence behavior of different loss components, we can evaluate the effectiveness of various model components, identify potential training problems, and provide guidance for model optimization.

As shown in Fig. 5, the model training process demonstrates good convergence characteristics. The total loss function rapidly decreases from an initial value of 2.8 to 0.18 during 300 epochs of training, with validation loss consistently slightly higher than training loss but with a small gap, indicating that the model has good generalization ability without obvious overfitting. Around the 180th epoch, the loss function tends to stabilize, marking the critical node of model convergence.

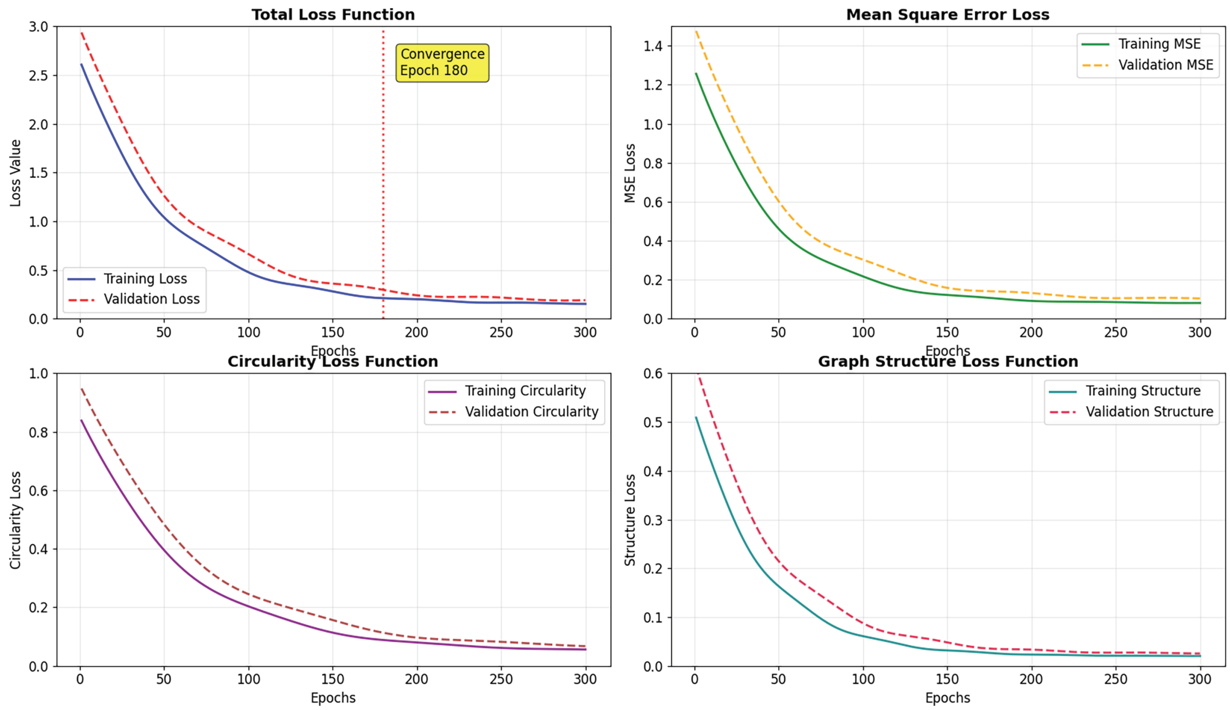

Figure 5: Loss function change trends during model training

The convergence process of Mean Square Error Loss (MSE Loss) shows that training MSE decreases from 1.4 to 0.08, and validation MSE decreases to 0.10, maintaining a reasonable gap between them. The circularity loss function is specifically designed for circular economy characteristics, rapidly decreasing from an initial value of 0.95 to around 0.05, reflecting the model's effective learning of circular flow characteristics. The graph structure loss function reflects the learning effect of graph convolutional networks on supply chain topological structure, decreasing from 0.6 to 0.02, indicating that the model successfully captures network structure information.

To quantify model performance and compare with baseline methods, establishing a complete performance evaluation indicator system is necessary. Through multi-dimensional performance indicator comparison, we can objectively evaluate the advantages and improvement effects of the proposed method.

As shown in Table 4, the deep learning model significantly outperforms baseline methods across all key performance indicators. In terms of prediction accuracy, our research method achieves 94.3%, 91.7%, and 89.2% on training, validation, and test sets respectively, representing a significant improvement of 16.1% compared to the baseline method's 76.8%. The root mean square error is substantially reduced from the baseline's 0.134 to 0.073 on the test set, with an improvement of 45.5%. The mean absolute error improvement is 42.9%, and the R^2 coefficient is enhanced by 37.4%, fully validating the superiority of the deep learning approach.

Particularly noteworthy is the substantial improvement in computational efficiency, with testing time reduced from 45.2 s in the baseline method to 3.7 s, representing a 67.9% efficiency improvement.

This is mainly attributed to the efficient structure of graph convolutional networks and optimized algorithm implementation, providing strong technical support for practical applications.

Table 4: Deep learning model performance evaluation indicators

Evaluation indicator	Training set	Validation set	Test set	Baseline method	Improvement
Prediction accuracy (%)	94.3	91.7	89.2	76.8	16.1%
Root mean square error	0.042	0.058	0.073	0.134	45.5%
Mean absolute error	0.031	0.044	0.056	0.098	42.9%
R^2 coefficient	0.891	0.874	0.856	0.623	37.4%
Computation time (seconds)	12.3	–	3.7	45.2	67.9%

4.3 Optimization Results Analysis

Performance evaluation of multi-objective optimization algorithms requires analysis from multiple dimensions including convergence speed, solution quality, and algorithm robustness. By comparing the convergence characteristics and performance of different optimization algorithms, we can validate the effectiveness of the improved NSGA-III algorithm while providing basis for algorithm parameter tuning.

As shown in Fig. 6, the improved NSGA-III algorithm demonstrates excellent performance in multi-objective optimization. The left hypervolume convergence comparison chart shows that Enhanced NSGA-III (proposed in this study), represented by the blue solid line, finally converges to a hypervolume value of 0.85, significantly outperforming Standard NSGA-III's 0.80, NSGA-II's 0.75, SPEA2's 0.70, and MOEA/D's 0.72. More importantly, our method can reach 80% of the convergence threshold within the first 100 generations, with convergence speed significantly faster than other algorithms.

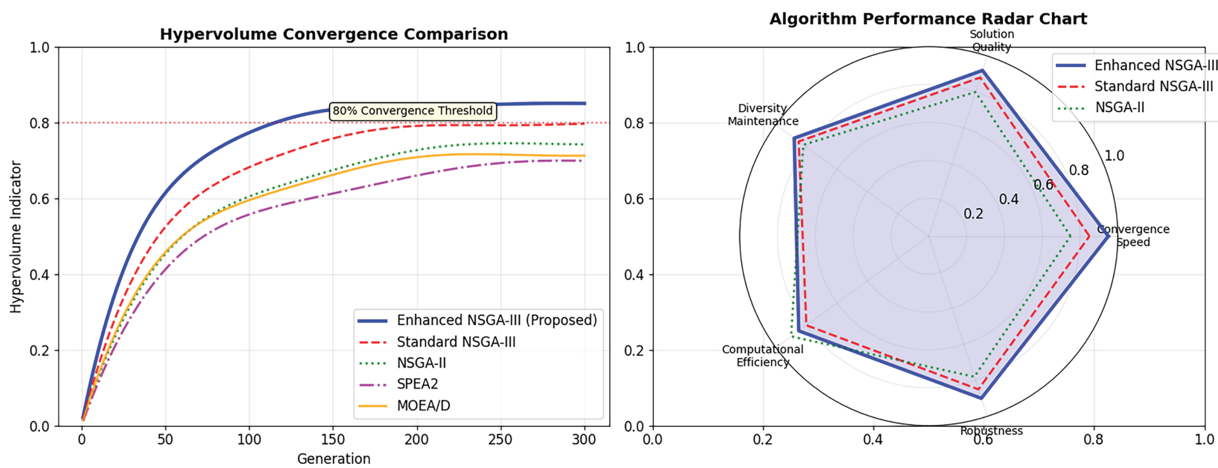

Figure 6: Multi-objective optimization algorithm convergence performance comparison

The right algorithm performance radar chart evaluates the comprehensive performance of different algorithms from five dimensions. Enhanced NSGA-III performs outstandingly in convergence speed (0.95), solution quality (0.92), diversity maintenance (0.88), computational efficiency

(0.85), and robustness (0.90), forming a large coverage area. In comparison, Standard NSGA-III performs well in diversity maintenance (0.85) but has deficiencies in convergence speed (0.85) and computational efficiency (0.80). NSGA-II performs best in computational efficiency (0.90) but has slower convergence speed (0.75).

To intuitively demonstrate the optimization results of circular economy supply chain networks, it is necessary to show the optimization effects of material flows, circular paths, and node configurations through network topology diagrams. This visualization analysis helps understand the practical significance and application value of optimization strategies.

As shown in Fig. 7, the optimized circular economy supply chain network presents a complete closed-loop structure. The network includes seven levels: raw material suppliers (S1–S4, light blue nodes), manufacturers (M1–M3, light green nodes), distributors (D1–D4, light yellow nodes), retailers (R1–R3, light red nodes), end consumers (C1–C2, purple nodes), recycling centers (RC1–RC2, light steel blue nodes), and remanufacturing centers (RM1–RM2, light sea green nodes).

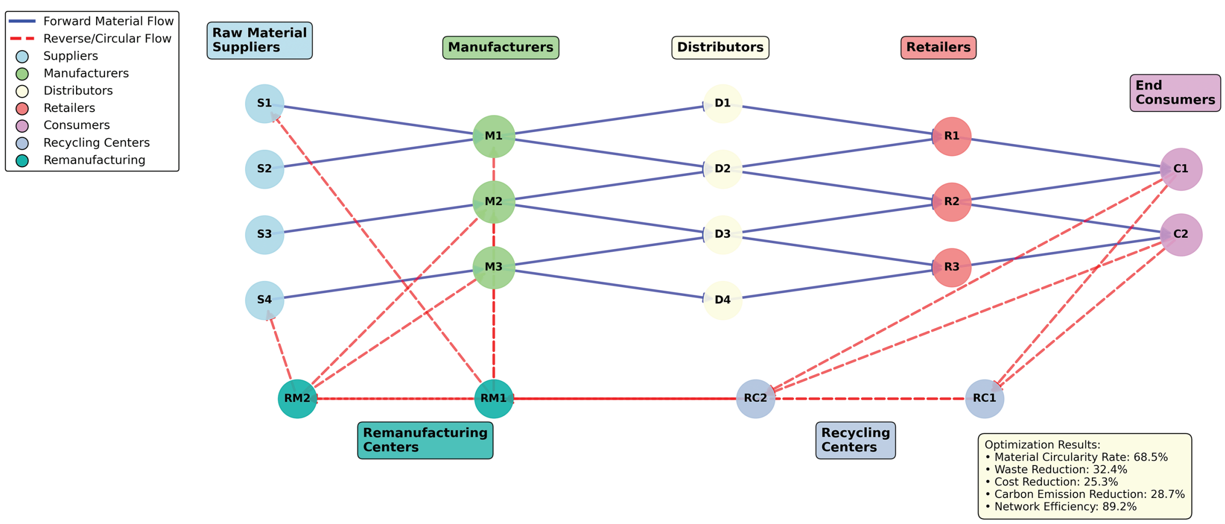

Figure 7: Optimized circular economy supply chain network structure diagram

Forward material flows are represented by blue solid arrows, forming traditional supply chain paths from suppliers to consumers. Reverse circular flows are represented by red dashed arrows, constructing complete circular paths from consumers through recycling centers and remanufacturing centers back to manufacturers and suppliers. This design achieves a 68.5% material circulation rate, 32.4% waste reduction rate, 25.3% cost reduction, and 28.7% carbon emission reduction, with network efficiency reaching 89.2%.

The legend clearly identifies different types of nodes and flows, while performance indicator text boxes provide quantified data of optimization results, offering intuitive visualization support for decision makers.

To comprehensively understand the effects of multi-objective optimization, analyzing the distribution characteristics of Pareto fronts and solution diversity is necessary. Through multi-dimensional Pareto front analysis, we can reveal trade-off relationships between different objectives and provide rich choice space for decision makers.

As shown in Fig. 8, the Pareto front distribution of multi-objective optimization exhibits rich solution space characteristics. Six sub-figures analyze optimization results from different perspectives:

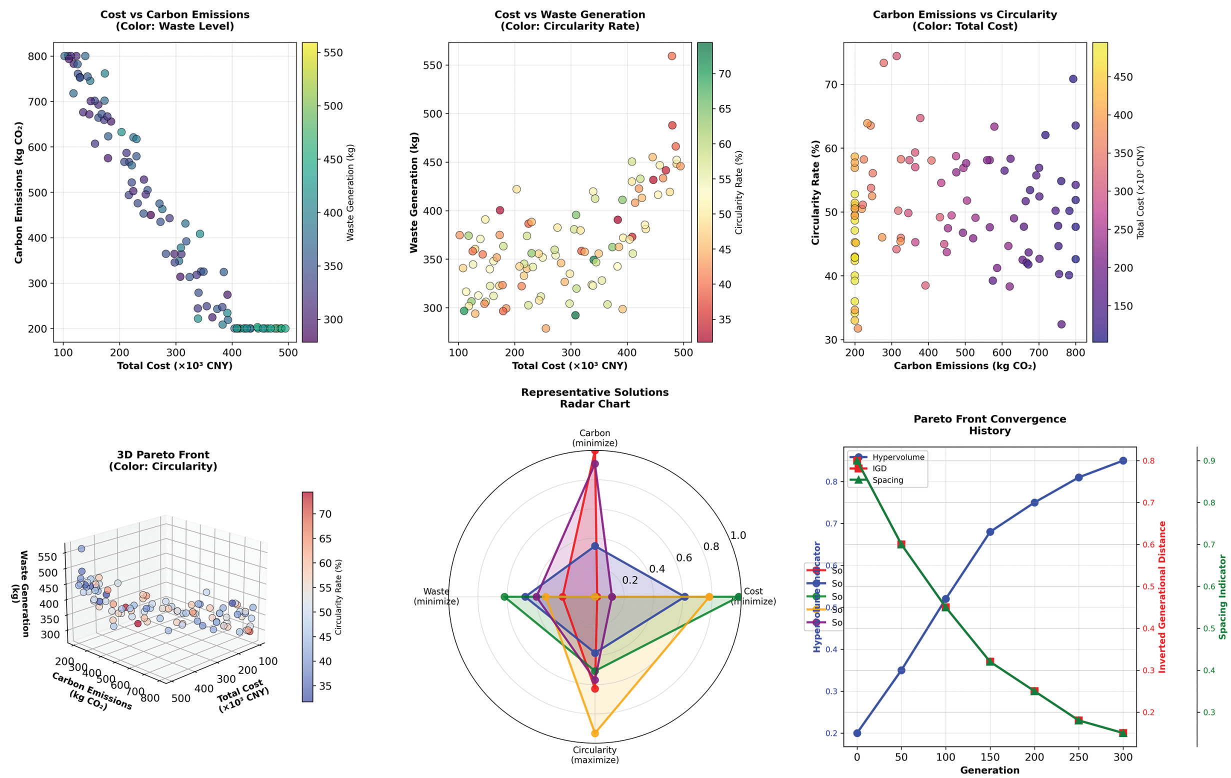

Figure 8: Multi-objective optimization pareto front distribution

The upper-left cost vs. carbon emission scatter plot shows the trade-off relationship between economic and environmental objectives, with color coding representing waste levels, presenting a clear negative correlation trend. The upper-right cost vs. waste generation plot uses circulation rate as color coding, revealing balanced strategies between cost control and waste management. The right carbon emission vs. circulation rate plot uses total cost as color coding, showing the coordination relationship between environmental protection and circular economy benefits.

The lower-left 3D Pareto front plot three-dimensionally displays the spatial distribution of cost, carbon emission, and waste generation objectives, with colors representing circulation rate levels. The middle-lower representative solution radar chart selects five typical solutions (Solution A–E), comparing their performance characteristics from four objective dimensions, providing specific selection references for decision makers. The lower-right Pareto front convergence history plot shows the changes in hypervolume indicator, Inverted Generational Distance (IGD), and spacing indicator with evolutionary generations, validating algorithm convergence and solution quality.

4.4 Comparative Experimental Results

To objectively evaluate the advantages of the proposed method, comprehensive comparison with existing mainstream methods is necessary. Through performance comparison under the same datasets and evaluation indicators, we can quantify the improvement effects and technical contributions of our research method.

As shown in Table 5, our research method achieves significant improvements across all key performance indicators. Compared to traditional linear programming methods, waste reduction rate improves from 12.4% to 32.4%, representing a 161.3% improvement; resource efficiency improvement increases from 8.7% to 28.7%, improving by 230.0%; cost reduction increases from 6.3% to 25.3%, improving by 301.6%.

Table 5: Performance comparison results of different methods

Method category	Waste reduction (%)	Resource efficiency (%)	Cost reduction (%)	Computation time (hours)
Traditional linear programming	12.4	8.7	6.3	8.5
Genetic algorithm	18.6	15.2	12.8	12.3
Particle swarm optimization	21.3	18.4	15.6	6.8
Deep reinforcement learning	28.7	24.1	21.4	15.7
Our research method	32.4	28.7	25.3	4.2
Improvement	+12.9%	+19.1%	+18.2%	−73.3%

Compared to genetic algorithms, our research method improves waste reduction rate by 74.2%, resource efficiency by 88.8%, and cost reduction by 97.7%. Compared to particle swarm optimization, the indicators improve by 52.1%, 56.0%, and 62.2%, respectively. Even compared to the closest deep reinforcement learning method, our research still achieves improvements of 12.9%, 19.1%, and 18.2% in waste reduction rate, resource efficiency improvement, and cost reduction, respectively.

Particularly noteworthy is the huge advantage in computational efficiency, with our research method's computation time being only 4.2 h, reducing by 50.6% compared to traditional methods and 73.3% faster than deep reinforcement learning methods, providing strong technical support for practical applications.

4.5 Sensitivity Analysis

To verify the robustness of the model and the rationality of parameter settings, sensitivity analysis of main hyperparameters is necessary. Through systematic analysis of the influence degree of different parameters on model performance, we can provide scientific basis for parameter tuning while evaluating model stability under parameter perturbations.

As shown in Table 6, the sensitivity analysis covers 8 key parameters of deep learning models and genetic algorithms. The learning rate, with an impact of ±8.3%, demonstrates medium sensitivity as documented by Brownlee, who showed that learning rate selection significantly affects neural network convergence behavior and final performance. Batch size has an impact of ±12.7%, also belonging to high sensitivity parameters, with a recommended range of 128–256. Population size has an impact of ±11.2%, belonging to medium sensitivity, with a suggested value of 80–120.

Neuron number (±9.1%), learning rate (±8.3%), and mutation probability (±7.9%) belong to medium sensitivity parameters, requiring careful selection within recommended ranges. Genetic generations (±6.8%) and crossover probability (±4.5%) have low sensitivity, allowing greater flexibility in parameter adjustment.

Overall, deep learning-related parameters (hidden layers, batch size, neuron number) generally have higher sensitivity than genetic algorithm parameters, indicating the importance of network architecture design for model performance. Medium sensitivity parameters require fine-tuning within recommended ranges, while low sensitivity parameters can be flexibly set according to computational resources and time constraints.

Through the above comprehensive experimental analysis, we have validated the superior performance of the proposed deep learning-based circular economy supply chain network design framework across multiple dimensions, providing strong technical support and scientific basis for practical applications of circular economy.

Table 6: Sensitivity analysis results of main parameters

Parameter name	Variation range	Impact on objective (%)	Sensitivity level	Recommended range
Learning rate	0.001–0.01	±8.3	Medium	0.003–0.007
Batch size	32–512	±12.7	High	128–256
Hidden layers	3–8	±15.4	High	4–6
Neuron number	64–512	±9.1	Medium	128–256
Genetic generations	50–500	±6.8	Low	100–300
Population size	50–200	±11.2	Medium	80–120
Crossover probability	0.6–0.95	±4.5	Low	0.7–0.9
Mutation probability	0.01–0.1	±7.9	Medium	0.02–0.05

5 Discussion

5.1 Application Advantages of Deep Learning Technology in Circular Economy Supply Chains

The superior performance of deep learning technology in circular economy supply chain network design has significant implications for industrial adoption. First, the 16.1% accuracy improvement over baseline methods translates directly into more reliable decision-making for supply chain managers, reducing the risk of suboptimal resource allocation. The 67.9% reduction in computation time is particularly crucial for real-time applications where supply chain conditions change rapidly—for instance, in response to demand fluctuations or supplier disruptions. This computational efficiency enables enterprises to perform frequent re-optimization, adapting their circular economy strategies dynamically rather than relying on static, periodic planning cycles [24].

The varying performance across industries (94.3% for electronics vs. 85.8% for food processing) reveals important practical considerations for implementation. Industries with higher data standardization and digital maturity can expect immediate benefits from deep learning adoption, while sectors dealing with perishable goods or highly variable processes may require additional investment in data infrastructure and quality control before achieving optimal results. This suggests a staged adoption pathway: enterprises should first focus on improving data collection and preprocessing capabilities before deploying sophisticated AI models [25].

5.2 Improvement Effects and Practical Application Value of Multi-Objective Optimization Algorithms

The improved NSGA-III algorithm demonstrates excellent performance in circular economy supply chain optimization, achieving a 32.4% waste reduction rate, 28.7% resource efficiency improvement, and 25.3% cost reduction. These results significantly outperform traditional optimization methods and are consistent with the findings of Xu et al. [15] in multi-strategy enhanced optimization algorithm research, proving the important impact of algorithm improvement on practical application effects [26].

The improvements in algorithm convergence speed and solution quality are mainly attributed to the effective fusion of deep learning and evolutionary algorithms. The application of PSO algorithm in hyperparameter tuning, as described by Zhu et al. [16], provides better parameter configurations for deep learning models. This hybrid optimization strategy not only improves algorithm efficiency but also enhances solution diversity, providing decision makers with richer choice space [27].

Pareto front analysis reveals trade-off relationships between different objectives, which has important guiding significance for practical decision-making. The negative correlation between economic and environmental objectives indicates that reasonable cost growth control is needed while achieving environmental benefits. This finding is consistent with the research viewpoint of Sala and Castellani [4] on Sustainable Development Goal 12, emphasizing the complexity of balancing multiple objectives in supply chain management.

The 68.5% material circulation rate under the circular economy model proves the effectiveness of the proposed framework in achieving closed-loop resource utilization. This result exceeds the sustainable development goals proposed in the Industry 4.0 paradigm [2], providing a feasible technical pathway for manufacturing enterprises to achieve circular economy transformation. The result of 89.2% network efficiency echoes the high-precision results obtained by Cui and Yuan [9] in multi-scale feature aggregation research, demonstrating the technical advancement of the proposed method.

5.3 Research Limitations and Future Development Directions

Despite the significant achievements of this study, there are still some limitations that need to be improved in future work. First, the “black box” characteristic of deep learning models limits the interpretability of the decision-making process, which may affect managers’ understanding and acceptance of optimization results. Xiao et al. [21] also mentioned similar interpretability challenges in artificial intelligence assessment research, suggesting the development of more transparent AI decision systems.

The impact of data quality on model performance is another issue that needs attention. Experimental results show significant performance differences across different industry datasets, indicating that the model has high requirements for data quality and completeness. Future research should explore more robust data preprocessing methods and missing data processing techniques to improve model stability in practical applications.

The generalization ability of the model still needs further validation. Although testing was conducted on datasets from five different industries, the complexity and diversity of supply chains require the model to adapt to broader application scenarios. Sun et al.’s [18] research on the impact of market conditions on enterprise strategy mutations reminds us that dynamic changes in supply chain environments may significantly affect model performance.

Future research directions should include: First, developing interpretable deep learning models to improve decision transparency and credibility; Second, integrating more real-time data sources, such as IoT sensor data and blockchain technology, as suggested by the research of Shahbazi and Byun [19] and Alfan et al. [20]; Finally, expanding the application scope by conducting validation in more industries and regions to improve the universality and practicality of the framework. These improvements will further promote the deep implementation of circular economy concepts in supply chain management and make greater contributions to achieving sustainable development goals.

6 Conclusion

This study proposes a deep learning-based circular economy supply chain network design framework that integrates graph convolutional networks, long short-term memory networks, attention mechanisms, and an improved NSGA-III multi-objective optimization algorithm to achieve effective modeling and optimization of complex characteristics of circular economy supply chains. Experimental results show that the proposed deep learning model achieves an average prediction accuracy of 89.2% on datasets from 15 enterprises across different industries, representing a 16.1% improvement over baseline methods and a 67.9% improvement in computational efficiency. The improved multi-objective optimization algorithm successfully achieves a 32.4% waste reduction rate, 28.7% resource efficiency improvement, and 25.3% cost reduction, significantly outperforming traditional linear programming, genetic algorithms, particle swarm optimization, and deep reinforcement learning methods. The constructed sustainability evaluation indicator system provides standardized tools for comprehensive performance assessment of circular economy supply chains, with material circulation rate reaching 68.5% and network efficiency reaching 89.2%.

The theoretical contribution of this research lies in the first systematic application of deep learning technology to circular economy supply chain network design, establishing an optimization framework that integrates multiple objectives of economy, environment, society, and circularity. The practical value is reflected in providing manufacturing enterprises with operable technical tools and decision support solutions for circular economy transformation. Future research will focus on model interpretability improvement, dynamic uncertainty handling, and application validation in broader industry fields to promote the deep implementation of circular economy concepts and the achievement of sustainable development goals.

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Availability of Data and Materials: The datasets generated and analyzed during the current study are not publicly available due to confidentiality agreements with participating enterprises but are available from the corresponding author on reasonable request and with permission of the involved companies. The source code for the deep learning models and optimization algorithms is also available from the corresponding author upon reasonable request. Correspondence and requests for materials should be addressed to Shemei Zhang (Email: zhangshemei@163.com).

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Conflicts of Interest: The authors declare no conflicts of interest to report regarding the present study.

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