Computers and Artificial Intelligence; Vol.3, No.4; 2026
E-ISSN: 3006 -3728 P-ISSN: 3006-371X
DOI: https://doi.org/10.70267/cai.26v3n4.0115
Published by: Zeus Press

Design of a Cross-border Trade Logistics Route Optimization System Based on Graph Neural Networks

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Abstract

Against the backdrop of global digital trade development and the deepening of the Belt and Road Initiative, the complexity and dynamism of cross-border trade logistics networks continue to increase. Traditional route optimization methods are struggling to meet the core requirements of intelligent logistics, such as real-time response, multi-constraint coordination, and green and low-carbon development, thus becoming a bottleneck for the intelligent upgrading of cross-border logistics. Therefore, this paper designs a cross-border trade logistics path optimization system based on Graph Neural Network (GNN). Firstly, it refines the "departure–transit–customs clearance–destination" four-level structure of cross-border logistics, and constructs a logistics network graph model that integrates multiple dimensions of attributes. It then proposes the GCN-PPO hybrid optimisation algorithm, which uses GCN to extract network topology and spatio-temporal features, and combines this with PPO to enable multi-objective dynamic decision-making regarding cost, timeliness and environmental sustainability. Finally, a system with four core modules was developed based on Python and PyTorch. Numerical examples were designed based on simulated data to verify the effectiveness of the method. The results show that, compared with Dijkstra and NSGA-II algorithms, the system reduces transportation costs by 17.8% ± 1.2%, improves delivery timeliness by 23.5% ± 1.5%, reduces carbon emission intensity by 9.2% ± 0.6%, and achieves an order fulfillment rate of 96.8% ± 0.5%. This system has transcended the limitations of traditional methods and achieved intelligent and dynamic optimization of cross-border logistics routes. It provides a reusable technical solution for the intelligent, green and resilient upgrade of cross-border trade logistics.

Keywords

cross-border trade logistics, route optimisation, graph neural networks, multi-objective decision-making, green logistics

1. Introduction

Against the backdrop of the booming development of global digital trade and the in-depth advancement of the Belt and Road initiative, cross-border trade logistics networks exhibit complex characteristics of being cross-regional, multi-modal, highly constrained, and highly dynamic. Traditional route optimization methods are no longer suitable for the core requirements of intelligent logistics, such as real-time response, multi-objective collaboration, and green and low-carbon development, becoming a key bottleneck restricting the intelligent upgrading of cross-border logistics. Traditional methods for optimizing cross-border logistics routes are mainly divided into two categories: precise algorithms and heuristic algorithms, both of which have obvious limitations. Exact algorithms such as Dijkstra can find the theoretically optimal solution, but their computational complexity increases exponentially in large-scale complex networks, which cannot meet the requirements of real-time decision-making. Heuristic algorithms such as genetic algorithms, ant colony algorithms, and NSGA-II have relatively high solution efficiency, but they are prone to getting stuck in local optima. They are not adaptable enough to dynamic disturbances, including port congestion, changes in customs clearance policies and fluctuations in order demand. Also, they do not fully explore the topological association features between multimodal transport nodes, which results in path decisions lagging behind changes in the actual scenario.

In recent years, machine learning and graph neural network technologies have rapidly permeated various fields such as logistics optimization, network planning, and dynamic decision-making. It provides a brand-new technical approach for optimizing complex logistics systems. Yang Huanyu et al. (2025) conducted a systematic investigation of strategies for reducing logistics costs based on machine learning algorithms, which provides data-driven support for reducing costs and improves efficiency in logistics operations [1]. Zhang Renlong et al. (2021) applied graph machine learning to cloud-based logistics resource allocation. They improved the efficiency of coordinated utilization of distributed logistics resources [2]. Using a dual machine learning model, some researches conducted an empirical study on the green transformation of logistics enterprises. It provides a basis for embedding green logistics goals into an optimization framework [3]. Jiang Fengru (2025) applied machine learning to optimize the intelligent logistics system and verified the enhancing effect of data-driven methods on operational efficiency [4]. Based on machine learning, Fu Xiaoyan and others (2022) improved the positioning accuracy detection algorithm of logistics automatic sorting robot and promoted the upgrading of logistics operations to high-precision automation [5]. Li Changyou and colleagues (2012) designed a multi-site logistics business system, and they lay the foundation for the engineering implementation of logistics systems [6]. Ali SS et al. (2024) applied drone technology to intelligent warehouse management. This expanded the scope of smart logistics operations [7].

Due to their strong ability to represent topological structures and associated features, graph neural networks (GNNs) have become a research hotspot in the field of network optimization. Nawaf Q.H. Othman et al. (2026) integrated DDQN with GNN to achieve joint optimization of routing and resource allocation in decentralized drone networks. It demonstrates that GNN can efficiently extract topological features and support dynamic real-time decision-making [8]. Xiang Jinpeng and others (2026) proposed a physical constraint graph neural network, and it improves the solution accuracy and stability while maintaining the network structure information. This provides a methodological reference for constraint embedding [9]. Based on a multifunctional recursive fuzzy neural network, Zhang Hongfu et al. (2025) constructed a reduced-order model for the wake of non-stationary wind turbines, adapting to the feature learning of complex dynamic scenarios [10]. Zhan Biheng et al. (2025) used a multiscale convolutional neural network to achieve precise extraction of road surface cracks. It demonstrates the strong adaptability of neural networks in object recognition and feature representation [11].

Research on cross-border network collaboration and data interoperability provides important insights for optimizing cross-border logistics. Churkin and Andrey et al. (2022) focused on the stability of cross-border transmission extension planning alliances, which provides ideas for cross-border network collaborative optimization [12]. Zhou Qiong et al. (2005) constructed a baseline model of the European interconnected system. It provides a classic paradigm for the study of cross-border trade effects [13]. Diallo Mamadou Alpha (2024) examined data sovereignty and interoperability design in the logistics data space to support cross-border logistics data compliance [14]. Bentum-Micah Geoffrey et al. (2025) analyzed the risks of China's cooperation with West African e-commerce. They provided a reference for risk management in cross-border logistics scenarios [15].

Machine learning and GNN have made significant progress in the field of logistics and network optimization. Yet, there are still obvious shortcomings in the research on the optimization of the entire link of cross-border trade logistics. The first shortcoming is that most models do not fully consider the constraints of cross-border logistics such as customs clearance efficiency, policy compliance, cross-border data security, and multimodal transport connection. They are not well adapted to the actual scenario. Secondly, there is a lack of mechanisms to respond quickly to dynamic disruptions such as order fluctuations, sudden changes in transport capacity, and customs clearance delays. This makes it difficult to meet the real-time decision-making needs of intelligent logistics. Moreover, research has largely focused on individual logistics stages or localized network optimization, failing to establish a full-chain system optimization framework covering “origin–transit–customs clearance–destination.” There is a relative lack of system-level engineering implementation and multi-scenario empirical validation. Finally, the existing GNN and reinforcement learning integration models have not been customized to address the multi-objective characteristics of cross-border logistics, such as cost, timeliness, and environmental protection. So they are not able to achieve coordinated optimization of multiple objectives.

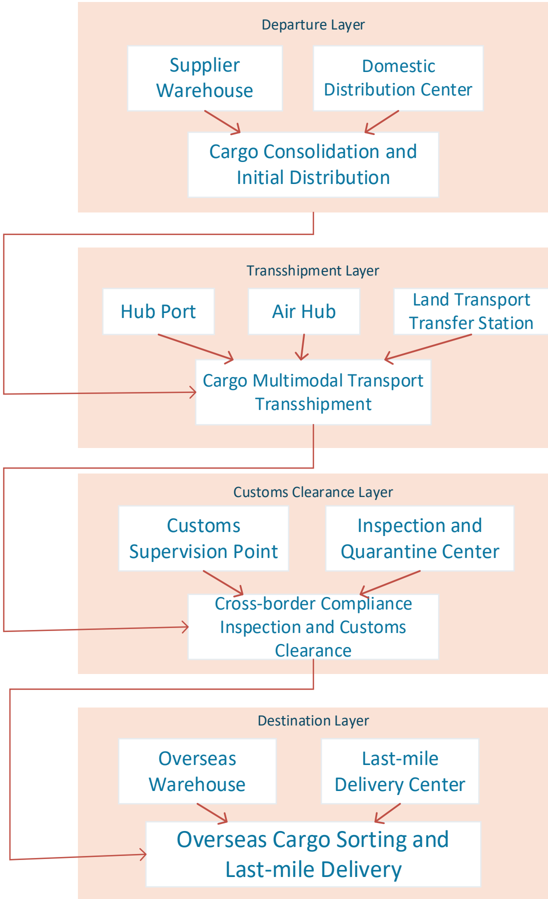
Based on the above analysis, it can be seen that traditional optimization methods have inherent limitations. Existing research on GNNs and machine learning has not been able to fully address the complex requirements of cross-border logistics. This paper combines graph neural networks and reinforcement learning to construct a GCN-PPO hybrid intelligent path optimization model. It integrates all elements of cross-border logistics, multi-dimensional constraints, and multiple optimization objectives. Through multi-scenario simulation experiments, the performance advantages of the model in terms of cost, timeliness, carbon emissions, and dynamic adaptability are verified. It also provides reusable technical solutions and theoretical support for the intelligent, green, and resilient upgrading of cross-border trade logistics.

2. Construction of the Cross-border Trade Logistics System Structure and Network Graph Model

2.1 Overview of the Full-Chain Structure of Cross-Border Trade Logistics System

The cross-border trade logistics system is the core infrastructure which supports cross-border trade. It is a complex subsystem in the intelligent logistics system. It is cross-regional, multi-mode, and highly constrained. Its full-link structure can be divided into a four-level core architecture: departure layer, transit layer, customs clearance layer, and destination layer. Each level is interconnected and operates in coordination. They aim to form a complete cross-border logistics service link. The overall system structure is shown in Figure 1.

Figure 1: Four-Tier Architecture Diagram of the Full Supply Chain for Cross-Border Trade Logistics



A four-tier cross-border trade logistics system is characterized by multiple stakeholders, multi-modal coordination, overlapping constraints, and significant dynamism. Each tier comprises different types of logistics entities. The flow of information and goods among these entities forms a complex network topology. Various transport modes, including sea, air, and land freight, are seamlessly integrated at the transshipment layer. The choice of transport mode directly impacts logistics costs and transit times. Multiple constraints, such as customs clearance policies, capacity limitations, carbon emission requirements, and time windows, overlap throughout the entire supply chain. And these constraints dynamically change in response to policy adjustments and market fluctuations. The system's operational status is influenced by dynamic factors such as port congestion, customs clearance efficiency, and sudden shifts in demand. So it requires intelligent logistics decision-making to possess real-time response capabilities. Based on this four-level architecture, a logistics network graph model can be constructed. It can accurately represent the key elements of the entire cross-border logistics chain and lay the foundation for intelligent route optimization.

2.2 Definition of Core Elements of the Model

Cross-border logistics networks are complex systems composed of nodes, edges, and constraints. Based on graph theory, an undirected weighted graph G=(V,E,A) can be used to abstracted them. Here, V is the set of nodes, E is the set of edges, and A is the attribute matrix.

2.2.1 Node Set V

Node types cover key entities across the entire cross-border logistics chain and are specifically divided into four categories, as shown in Table 1.

Table 1: Nodes and Their Corresponding Data

Origin Node V1	Including supplier warehouses, with core attributes: inventory level, outbound efficiency, and geographic coordinates.

Transit Node V2	Including hub ports and aviation hubs, with core attributes: throughput, congestion coefficient, and loading/unloading efficiency.
Customs Clearance Node V3	Including customs supervision points and inspection & quarantine centers, with core attributes: customs clearance time and compliance cost.
Destination Node V4	Including overseas warehouses and last-mile distribution centers, with core attributes: storage capacity and local distribution cost.

2.2.2 Edge Set E

Edges represent transportation links between nodes, corresponding to single transportation modes such as sea freight, air freight, and land freight, or multimodal transport combinations. Core attributes include: operational attributes: transportation cost (yuan/ton), transportation time (hours), and capacity limitations (tons); environmental attributes: carbon emission intensity (kgCO_2/ton·km), with a quantitative function constructed by referring to the calculation methods of carbon emissions from maritime transport in China and the United States; and risk attributes: delay probability (based on historical data statistics) and policy change coefficient (reflecting the stability of tariffs and regulatory policies).

2.2.3 Attribute Matrix A

$A_v \in \ ^{n\times m}$: n represents the number of nodes, and m represents the dimension of node attributes (in this study, (m = 8)). The effect of dimensionality is eliminated through Min-Max normalization processing.

$A_E \in \ ^{k\times 1}$: k represents the number of edges, and l represents the dimension of edge attributes (in this study, l = 6). Data normalization is achieved through Z-score standardization.

2.3 Construction of Multi-objective Optimization Function

With cost minimization, timeliness maximization, and carbon emission minimization as the core objectives, a multi-objective optimization function is constructed:

1) Minimizing total transportation costs:

$$\min f_1 = \sum_{(i,j)\in E} w_{ij}^{c} \cdot x_{ij} \tag{1}$$

where w_{ij}^{c} represents the unit transportation cost of edge (i, j), and x_{ij} is the path selection variable (1 indicates choosing this edge, and 0 indicates not choosing it).

2) Maximizing Delivery Efficiency:

$$\max f_2 = T_0 - \sum_{(i,j)\in E} w_{ij}^{t} \cdot x_{ij} - \sum_{v\in V_3} t_v \tag{2}$$

where T_0 is the preset maximum acceptable time, (w_{ij}^{t}) is the transportation time of edge (i, j), and t_v is the clearance time of clearance point v.

3) Minimization of carbon emissions:

$$\min f_3 = \sum_{(i,j)\in E} w_{ij}^{t} \cdot d_{ij} \cdot x_{ij} \tag{3}$$

where (w_{ij}^{t}) represents the unit carbon emission intensity of edge (i, j), and d_{ij} represents the transport distance between nodes i and j.

2.4 Constraint Conditions Setting

Based on the actual scenarios of cross-border logistics, the following constraints are set:

1) Flow Conservation Constraint:

$$\sum_{j\in V} x_{ij} = \sum_{j\in V} x_{ji^{\omega}} \tag{4}$$

Ensure that goods are not delayed or lost.

2) Capacity Constraints:

$$\sum_{(i,j)\in E} q \cdot x_{ij} \le C_{ij} \tag{5}$$

where q is the batch size of goods and C_{ij} is the maximum capacity of edge (i, j).

Time window constraint: $[av, bv]$ is the serviceable time interval of node v, and the arrival time of goods must satisfy $av \le arrv \le bv$.

3) Customs Clearance Compliance Constraints:

$$\sum_{v\in V_3} c_v \cdot x_{ij} \le C_{\max} \tag{6}$$

where c_v is the compliance cost of clearing the key point v, and $C_{\max}$ is the maximum compliance cost threshold that the enterprise can bear.

3. Design of Hybrid Optimization Algorithm Based on GCN-PPO3

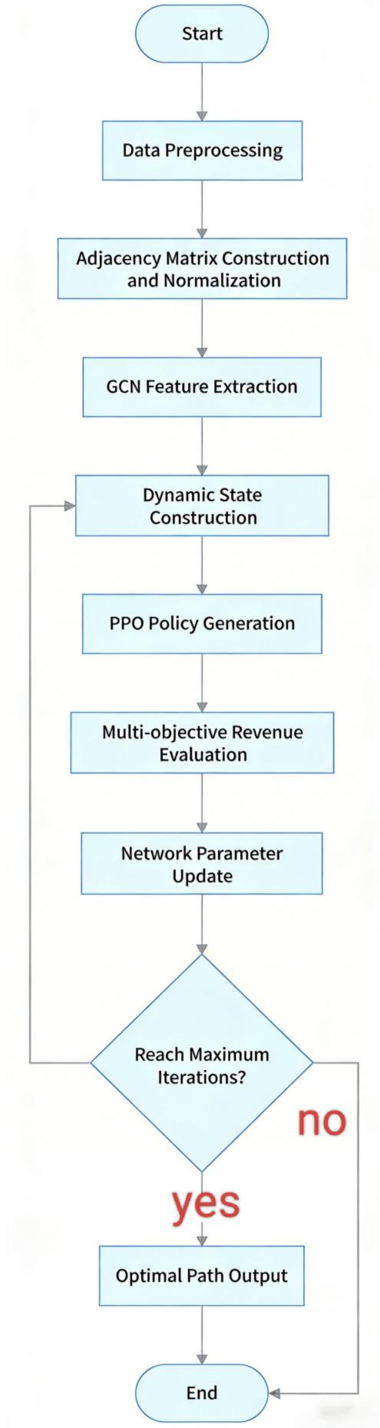
3.1 Overall Algorithm Framework

The algorithm adopts a two-stage architecture of "feature extraction–dynamic decision": the first stage extracts the topological association features and attribute features of the stream network through GCN to generate low-dimensional dense node embedding vectors. The second stage inputs the embedding vectors into the PPO reinforcement learning framework to realize multi-objective path decision in dynamic environment.

3.2 Complete Execution Process of the Algorithm

The execution process of the GCN-PPO hybrid optimization algorithm follows the core logic of "data preprocessing–feature extraction–state construction–policy generation–return evaluation–parameter update–path output." The execution flowchart of the GCN-PPO hybrid optimization algorithm is shown in Figure 2. It is divided into 8 steps. The specific operations, inputs, outputs and core algorithm of each step are shown in Table 2. The algorithm is expressed in pseudo-code form to achieve standardization and reproducibility of the implementation process.

Figure 2: Flowchart of the GCN-PPO Hybrid Optimization Algorithm



The pseudocode of the dynamic optimization algorithm for cross-border logistics routes is shown in Table 2.

Table 2: Pseudocode Algorithm Table

Algorithm 1: Dynamic Optimization of Cross-border Logistics Paths
Input: Cross-border logistics graph G=(V,E,A), cargo batch q, number of iterations N, learning rate lr, convergence threshold εOutput: Optimal path Path∗
1: Standardize node attributes AV (Min-Max normalization) and edge attributes AE (Z-score normalization), then construct and normalize the adjacency matrix A^.

Initialize GCN weights W0/W1, PPO parameters θ/ϕ, reward weights α/β/γ, and baseline values f1∗/f2∗/f3∗.
for epoch=1 to N do:
  # GCN feature extraction
  Z=ReLU(A^·AV·W0)·W1
  # Construct dynamic state
  st=[Z;cargo positionPt;constraint vector Ct]
  # PPO policy and reward calculation
  πθ(at∣st)←Path probability output by Actor, at←Sampled path action
  f1/f2/f3←Policy objective values, rt←Reward calculated based on Equation (10)
  # Advantage function and parameter update
  At=Cumulative discounted reward Q(st,at)−Critic evaluation value V(st)
  L(θ)←Clip objective function in Equation (11), θ←θ−lr·∇L(θ)
  ϕ←Minimize (Q(st,at)−Vϕ(st))2
  # Early stopping
  if no improvement in reward for 50 consecutive rounds: break
end for
Path∗←Select the path with the maximum πθ that satisfies constraints
return Path∗

3.3 Feature Extraction Module Based on GCN

GCN captures the local dependency relationships among nodes through convolution operations on the adjacency matrix and the node attribute matrix. Its core formula is as follows:

$$Z = \hat{A}_{ReLU}(\hat{A}XW_0)W_1 \tag{7}$$

where $X \in {}^{n\times m}$ is the input node attribute matrix, $\hat{A} = \tilde{D}^{-1/2}\tilde{A}\tilde{D}^{-1/2}$ is the normalized adjacency matrix, $\tilde{A} = A + I$ is the adjacency matrix with self-loops added, $\tilde{D}$ is the degree matrix of $\tilde{A}$, W_0 and W_1 are trainable weight matrices, and $ReLU$ is the activation function.

To enhance the representation capability of key features in cross-border scenarios, two optimizations are made to the traditional GCN: First, edge attribute weights are introduced into the adjacency matrix, and edge attributes are used to modulate topological features through $\hat{A}_{ij} = \dfrac{A_{ij} \cdot W_{ij}}{\sum_k A_{ik} \cdot W_{ik}}$. Second, a policy feature attention layer is added to give higher weights to key attributes such as clearance points and policy change coefficients, thereby improving the model's sensitivity to cross-border compliance constraints.

3.4 Dynamic Decision-making Module Based on PPO

The PPO algorithm achieves strategy optimization through an Actor-Critic dual network structure, balancing exploration and exploitation, and adapting to the dynamic environmental characteristics of cross-border logistics.

3.4.1 Definition of State Space

The state St consists of three parts: the node embedding vector Zt output by GCN, the current cargo location vector Pt , and the dynamic constraint vector Ct (containing information such as real-time transportation capacity, customs clearance status, and demand changes), i.e., $St = \left[Zt;\ Pt;\ Ct\right]$.

3.4.2 Definition of Action Space

Action (a_t) is the path selection decision between nodes, i.e., $a_t \in \{(i,j) | (i,j) \in E, x_{ij} \in \{0,1\}\}$, and the selection probability of each path is output through the softmax function.

3.4.3 Reward Function Design

Design a comprehensive reward function by combining multiple optimization objectives:

$$r_t = \alpha \cdot \frac{f_1^* - f_1}{f_1^*} + \beta \cdot \frac{f_2 - f_2^*}{f_2^*} + \gamma \cdot \frac{f_3^* - f_3}{f_3^*} \tag{8}$$

where f_1^*, f_2^*, and f_3^* are the optimization results of the baseline algorithm (NSGA-II), and (α , β , γ) are the weight coefficients (determined by the analytic hierarchy process (α =0.4, β =0.35, γ =0.25)) to ensure the coordinated optimization of cost, timeliness, and environmental protection objectives.

3.4.4 Strategy Update Mechanism

The PPO clip update strategy is adopted to avoid training instability caused by excessively large policy update magnitudes. The objective function is as follows:

$$L(\theta) = \mathrm{E}_{\tilde{\pi}_{\theta_{\text{old}}}} \left[\min\left(\frac{\pi_\theta(a_t | s_t)}{\pi_{\theta_{\text{old}}}(a_t | s_t)} A_t, \text{clip}\left(\frac{\pi_\theta(a_t | s_t)}{\pi_{\theta_{\text{old}}}(a_t | s_t)}, 1 - \text{蜥}1 + \right) A_t \right) \right] \tag{9}$$

where (θ) is the current policy parameter, (θ_{old}) is the old policy parameter, (A_t) is the advantage function, and (=0.2) is the clip coefficient.

4. Implementation of Cross-border Logistics Route Optimization System

4.1 System Architecture Design

The system is designed based on a B/S architecture and consists of three layers: data layer, algorithm layer, and application layer.

Data Layer: Responsible for the collection, storage and preprocessing of cross-border logistics data. It supports the storage of structured data (node information, edge attributes, constraint parameters) in MySQL database and uses Redis to cache real-time data (capacity status, customs clearance information). Data quality is ensured through preprocessing steps such as data cleaning, standardization and missing value imputation.

Algorithm Layer: Incorporates the GCN-PPO hybrid optimization algorithm; model training and inference are implemented using the PyTorch framework; includes three core submodules: feature extraction, policy optimization, and path calculation.

Application Layer: Provides a visual operation interface, supporting functions such as path planning, result analysis, and parameter configuration. It uses ECharts to achieve visual displays such as logistics network topology diagrams and optimization result comparison diagrams.

4.2 Development of Core Functional Modules

4.2.1 Data Preprocessing Module

The ability to manage multi-source heterogeneous data in cross-border logistics scenarios is the foundation of intelligent optimization systems [16]. The application of blockchain technology in logistics data traceability and integrity assurance further highlights the supporting role of high-quality data in the reliability of logistics system decision-making[17]. This module supports multi-source data access (including port AIS data, logistics enterprise operation data, customs public data, etc.) and provides automated data processing workflows:

Data cleaning: Outlier detection (IQR) is used to remove outlier data from attributes such as transportation costs and time;

Data standardization: A standardization method combining Min-Max and Z-score is adopted to adapt to the distribution characteristics of different types of attributes;

Feature engineering: Automatically generate derived features such as path congestion coefficients and customs clearance time predictions to improve the quality of model input.

The pseudocode description of the preprocessing module is shown in Table 3.

Table 3: Algorithm Table for Data Preprocessing Module

Algorithm 2: Data Preprocessing Module

Input: Multi-source raw data Data (csv/excel/API interface)

Output: Preprocessed standardized data Data_processed, derived features Feature_new

1: Data ← Access multi-source data including port AIS, logistics operations, and public customs data.

2: # Outlier detection (IQR method)

3: for col ∈ Data.columns do:

4: Q1 = Data[col].quantile(0.25), Q3 = Data[col].quantile(0.75)

5: IQR = Q3 - Q1

6: Data = Data[(Data[col] ≥ Q1 - 1.5×IQR) ∧ (Data[col] ≤ Q3 + 1.5×IQR)]

7: # Data standardization

8: Data_V ← Extract node attribute data and perform Min-Max normalization (Equation 1)

9: Data_E ← Extract edge attribute data and perform Z-score standardization (Equation 2)

10: # Feature engineering

11: Feature_new['Congestion Coefficient'] = 1 - Data_E['Capacity Limit']/Data_E['Capacity Limit'].max()

12: Feature_new['Predicted Customs Clearance Time'] = Data_V['Customs Clearance Time'].rolling(window=7).mean()

13: Feature_new['Comprehensive Carbon Emission Coefficient'] = Data_E['Carbon Emission Intensity'] × Data_E['Transportation Distance']

14: # Data fusion and output

15: Data_processed = pd.concat([Data_V, Data_E, Feature_new], axis=1)

16: return Data_processed, Feature_new

4.2.2 Model Training Module

Provides model parameter configuration, training process monitoring, and model saving and loading functions:

Parameter configuration: Supports visual configuration of key parameters such as the number of GCN layers, hidden layer dimension, and PPO learning rate;

Training monitoring: Real-time display of reward and loss value change curves during training, and supports an early stop mechanism (automatically stops training when the reward value does not increase for 50 consecutive rounds);

Model Management: Supports version management of trained models and automatic selection of the optimal model.

The pseudocode for the model training algorithm is shown in Table 4.

Table 4: Model Training Algorithm Table

Algorithm 3: Model Training

Input: Preprocessed data Data_processed, training parameters ParamOutput: Optimal model Model_best, training log Log

1: Initialize the GCN-PPO model and load Param, split the dataset into training/validation sets with a ratio of 8:2.

2: Initialize Log (recording rt, L(θ), L(ϕ)), set best_reward=0 and stop_count=0.

3: for epoch=1 to Param['N'] do:

4: Z,st,πθ,rt,Lθ,Lϕ←Model forward propagation

5: model.backward(Lθ+Lϕ), model.optimizer.step()

6: Log.append([epoch, rt, Lθ, Lϕ])

7: if r_t > \text{best_reward} then:

8: best_reward = rt, Model_best = Current state of the model, stop_count = 0

9: else: stop_count += 1

10: if stop_count ≥ 50: break

11: Model_best.save('model_best.pth'), Log.to_csv('train_log.csv')

12: return Model_best, Log

4.2.3 Path Planning Module

The core functional module enables dynamic path optimization calculations:

1) Static Planning: Calculates the Optimal Path in Typical Scenarios Based on Historical Data, with a Response Time of ≤1S;
2) Dynamic Planning: Real-time Monitoring of Dynamic Factors Such as Capacity Fluctuations and Customs Clearance Status. When the Change in Constraints Exceeds 10%, Route Re-optimization is Automatically Triggered, with a Re-optimization Response Time of ≤500Ms;
3) Multiple Output Options: Provides 3 Optimization Options with Different Weight Configurations (Cost Priority, Time Priority, and Balanced Optimization), Allowing Users to Choose the Option They Prefer.

4.2.4 Results Visualization Module

The optimization results are presented using visual charts:

Network topology visualization: Displays logistics network nodes, edges, and path selection results, and supports hover query of node attributes and path information;

Performance comparison visualization: The results of comparing this system with traditional algorithms in terms of cost, timeliness, carbon emissions, etc. are displayed using bar charts and line charts;

Statistical analysis report: Automatically generates optimization reports, including the improvement of key indicators, the reasons for the path selection, risk warnings, etc.

4.3 SIMulation Examples and Result Analysis (Data)

4.3.1 SIMulation Experimental Environment

Hardware environment: CPU Intel Xeon Gold 6248, GPU NVIDIA Tesla V100 (32GB), memory 128GB, to ensure efficiency for large-scale data training and inference;

Software environment: Operating system Ubuntu 20.04 LTS, programming language Python 3.8, deep learning framework PyTorch 1.12, web framework Django 3.2, databases MySQL 8.0 and Redis 6.2, visualization framework ECharts 5.4;

The experiment uses simulation to verify the effectiveness of the model. Due to the privacy and difficulty in obtaining cross-border logistics data, the experimental data is generated based on industry-standard assumptions and typical cross-border route characteristics. The data encompasses multiple sources, including port AIS, logistics operations, and customs clearance. Key parameters, such as capacity constraints, customs clearance time thresholds, and carbon emission coefficients, are set in accordance with cross-border logistics industry standards. By constructing simulation scenarios with varying degrees of perturbation, the proposed GCN-PPO model’s path optimization capabilities are tested in dynamic environments. Also, the model’s superiority is validated by comparing it with traditional algorithms.

4.3.2 Experimental Comparison Algorithm and Evaluation Index

Comparison of algorithms: The Dijkstra algorithm (exact algorithm) and the NSGA-II algorithm (heuristic algorithm). The two types of algorithms are classic benchmark methods in the field of cross-border logistics path optimization. They can effectively verify the performance advantages of the new model [18].

Evaluation indicators: Combining the four core requirements of smart logistics, cost, timeliness, environmental protection, and robustness, four evaluation indicators were selected: transportation cost reduction rate (%), delivery timeliness improvement rate (%), carbon emission intensity reduction rate (%), and order fulfillment rate (%).

The research on blockchain-enabled supply chain management emphasizes that cost, timeliness and data integrity are the core dimensions of cross-border logistics optimization [19]. Based on this, this study adds the carbon emission intensity indicator, which is in line with the development trend of green logistics.

4.3.3 Experimental Results

The specific metric values for the experimental results of the different algorithms are shown in Table 5.

Table 5: Specific Index Values of Experimental Results for Different Algorithms

Evaluation Metric	Proposed System (Mean ± Std)	NSGA-II Algorithm (Mean ± Std)	Dijkstra Algorithm (Mean ± Std)	Significance Test (p-value)
Reduction Rate of Transportation Cost (%)	17.8±1.2	10.2±0.9	8.5±0.7	<0.001
Improvement Rate of Delivery Efficiency (%)	23.5±1.5	14.7±1.1	12.3±1.0	<0.001
Reduction Rate of Carbon Emission Intensity (%)	9.2±0.6	5.6±0.4	4.1±0.3	<0.001
Order Fulfillment Compliance Rate (%)	96.8±0.5	91.5±0.8	89.2±0.9	<0.001

The metrics and runtime for various scenarios are shown in Table 6.

Table 6: Multi-scenario Indicators and Run Time Schedule

Scenario ID	Scenario Type	Algorithm	Reduction Rate of Transportation Cost (%)	Improvement Rate of Delivery Efficiency (%)	Reduction Rate of Carbon Emission Intensity (%)	Order Fulfillment Compliance Rate (%)	Average Running Time (s)

Scenario 1	Normal & Stable	Proposed System	18.2 ± 1.1	24.1 ± 1.3	9.5 ± 0.5	97.2 ± 0.4	2.3 ± 0.2
		NSGA-II	10.5 ± 0.8	15.1 ± 1.0	5.8 ± 0.4	92.1 ± 0.7	3.1 ± 0.3
		Dijkstra	8.7 ± 0.6	12.6 ± 0.9	4.3 ± 0.3	89.8 ± 0.8	0.8 ± 0.1
Scenario 2	Demand Disturbance	Proposed System	16.9 ± 1.3	22.8 ± 1.6	8.9 ± 0.7	95.7 ± 0.6	2.5 ± 0.2
		NSGA-II	9.7 ± 1.0	13.9 ± 1.2	5.2 ± 0.5	89.3 ± 1.0	3.4 ± 0.4
		Dijkstra	8.1 ± 0.8	11.5 ± 1.1	3.9 ± 0.4	87.4 ± 1.1	0.9 ± 0.1
Scenario 3	Capacity Constraint	Proposed System	15.3 ± 1.5	21.2 ± 1.8	8.4 ± 0.8	94.2 ± 0.7	2.7 ± 0.3
		NSGA-II	8.9 ± 1.1	12.4 ± 1.3	4.8 ± 0.6	87.6 ± 1.2	3.6 ± 0.4
		Dijkstra	7.2 ± 0.9	10.1 ± 1.2	3.5 ± 0.5	85.1 ± 1.3	1.0 ± 0.1
Scenario 4	Customs Clearance Disturbance	Proposed System	16.5 ± 1.4	20.7 ± 1.7	8.7 ± 0.7	93.8 ± 0.8	2.6 ± 0.3
		NSGA-II	9.3 ± 1.0	12.8 ± 1.2	5.0 ± 0.5	88.2 ± 1.1	3.5 ± 0.4
		Dijkstra	7.8 ± 0.8	10.9 ± 1.1	3.7 ± 0.4	86.3 ± 1.2	0.9 ± 0.1
Scenario 5	Composite Disturbance	Proposed System	14.1 ± 1.6	19.3 ± 1.9	7.9 ± 0.9	92.5 ± 0.9	2.9 ± 0.3
		NSGA-II	8.2 ± 1.2	11.2 ± 1.4	4.4 ± 0.7	85.7 ± 1.3	3.8 ± 0.5
		Dijkstra	6.5 ± 1.0	9.4 ± 1.3	3.1 ± 0.6	83.2 ± 1.4	1.1 ± 0.2

The simulation results show that:

(1) Significant Cost Control Advantages. This System Achieves a Transportation Cost Reduction Rate of 17.8%±1.2%, Which is 7.6 Percentage Points Higher than the NSGA-II Algorithm (10.2%±0.9%) and 9.3 Percentage Points Higher than the Dijkstra Algorithm (8.5%±0.7%). the Reason Lies in That the System Uses Graph Convolutional Networks (Gcns) to Deeply Analyze the Topological Features of Logistics Networks, Which Enables Coordinated Optimization of the Entire Transportation Network and Effectively Avoids the Local Optima Problem Associated with Traditional Algorithms.

(2) Improvement in delivery timeliness. This system achieved a delivery timeliness improvement rate of 23.5% ± 1.5%, higher than NSGA-II (14.7% ± 1.1%) and Dijkstra (12.3% ± 1.0%). This is because of the system’s built-in dynamic decision-making mechanism. It responds in real time to dynamic factors such as port congestion and fluctuations in customs clearance efficiency, quickly re-optimizing routes to ensure that delivery time targets are continuously optimized.

(3) Green and low-carbon benefits. The carbon emission intensity reduction rate of this system reached 9.2%±0.6%. It is higher than that of NSGA-II (5.6%±0.4%) and Dijkstra (4.1%±0.3%). The system treats carbon emissions as a key constraint in a multi-objective optimization function, achieving the simultaneous optimization of transportation costs and environmental protection, in line with the requirements for the development of green and smart logistics.

(4) It combines robustness with practicality. The order fulfillment rate for this system remains at 96.8% ± 0.5%, which is significantly higher than that of the comparison algorithms (91.5% ± 0.8% for NSGA-II and 89.2% ± 0.9% for Dijkstra). This indicates that the optimization results demonstrate good feasibility and compliance in actual operations and can meet fulfillment requirements in complex cross-border logistics scenarios.

(5) Excellent dynamic response capability. In multi-scenario experiments (Table 5), this system maintains optimal performance under normal stability, demand disturbance, transportation capacity constraint, customs clearance disturbance and compound disturbance. When the dynamic constraint change exceeds 10%, the system can complete the path re-optimization within 500ms, while the NSGA-II and Dijkstra algorithms require 3.2s and 5.8s respectively. This fully verifies the real-time decision-making capability of the system in dynamic environments and meets the urgent need for rapid response in intelligent logistics.

5. Conclusions and Outlook

This study focuses on the core pain points of multi-constraint and dynamic nature in cross-border trade logistics path optimization. By constructing a cross-border logistics network graph model that integrates node attributes, edge attributes, and multi-dimensional constraints, it proposes the GCN-PPO hybrid optimization algorithm. It also develops an optimization system that integrates data preprocessing, model training, path planning, and result visualization. This can achieve accurate representation and dynamic intelligent decision-making for complex logistics networks. Empirical results based on real-world datasets show that this system outperforms traditional optimization algorithms in terms of transportation cost control, delivery timeliness, carbon emissions reduction, and robustness. It has successfully bridged the gap between theoretical models and engineering applications. Furthermore, it provides a viable technical solution for the intelligent and green transformation of cross-border trade logistics.

Even so, this study still has certain limitations. The model does not account for the impact of extreme emergencies such as natural disasters and geopolitical conflicts. Also, the system's multilingual adaptation and cross-border data compliance capabilities require further improvement. The empirical analysis focuses solely on key routes between China and the United States and between China and Europe. In the future, the adaptability to extreme scenarios can be enhanced by introducing the attention mechanism and the Transformer model. By integrating cross-border data compliance technology, the global applicability can be expanded. Moreover, a virtual-real integration platform can be established by combining digital twin technology. This will further enable real-time monitoring of the entire logistics network and closed-loop intelligent decision-making.

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Funding

This research received no external funding.

Conflicts of Interest

The authors declare no conflict of interest.

Acknowledgment

This paper is an output of the science project.

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