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Real Time Multimodal Route Optimization and Anomaly Detection for Cross Border Logistics Using Deep Reinforcement Learning

Yue Xi[1], Xuzhong Jia[2] , Hanqing Zhang[3]
[1] Information Systems, Northeastern Unversity, WA, USA
[2] Computer Application Technology, Hunan University of Technology, HuNan, China
[3] Master of Science in Information Studies, Trine University, CA, USA
*Corresponding author E-mail: rexcarry036@gmail.com

Abstract*—This paper presents a new approach to improve multiple choice and defect detection in cross-border shipments using deep learning (DRL). The design process involves the integration of real-time data from multiple sources to create comprehensive transportation models, including route optimization, cost reduction, and poor research methods. The DRL project is intended to use a multi-agent design to manage complex decision-making processes in a dynamic logistics environment. The hybrid anomaly detection system combines statistics with machine learning techniques to identify and respond to network disruptions. The system's performance was validated using a database including 185,432 shipment records collected over 24 months across the Asia-Pacific transportation system. The experimental results show that the proposed method has achieved 94.5% correct value in choosing the right path and 45% reduction in processing time compared to traditional methods. The negative detection antibody maintains a 96.2% true positive rate with a 1.8% false positive rate. The system's analysis shows that the growth of the needs in the calculation of the growth in the network, indicating the use of good resources in the large deployment. This research supports the state-of-the-art in cross-border business optimization by providing solutions that integrate real-time optimization methods with negative detection and response mechanisms.*

Keywords: Deep Reinforcement Learning, Cross-border Logistics, Multimodal Transportation Optimization, Anomaly Detection

I. INTRODUCTION

1.1. Research Background and Significance

The rapid development of cross-border e-commerce has brought unprecedented challenges and opportunities for transportation in the transportation industry. The global logistics industry has experienced significant growth, with the global economy increasing exponentially[1]. Cross-border business involves easy transportation, many stakeholders, and different modes of transportation, making the process of improving efficiency a challenge for service providers. logistics service[2].

The logistics system plans the attack to meet the requirements of modern transportation across the border. These events are characterized by changes in traffic conditions, customs uncertainty, and various related obstacles. The integration of multimodal transport further affects the optimization process, requiring sophisticated decision-making processes to manage real-time adjustments and fault detection[3].

The advancement of advanced technology, especially deep learning (DRL), has opened up new possibilities to solve complex logistics optimization problems. DRL's ability to learn the right rules by interacting with the environment makes it particularly suitable for handling the dynamics and uncertainties of cross-border logistics[4]. The combination of DRL with the development of multimodal transport presents a good way to improve the efficiency and reliability of cross-border operations.

1.2. Literature Review

Previous research in cross-border logistics optimization has primarily focused on static route planning and single-modal transportation scenarios.

Liu et al. proposed an improved deep reinforcement learning approach for intelligent logistics supply chain transportation decision models, demonstrating the potential of DRL in logistics optimization[5]. Their work established a framework for incorporating real-time environmental information and dynamic decision-making capabilities.

In the domain of multimodal transportation, Jiang and Wu developed an optimization algorithm for logistics distribution paths based on deep learning, addressing the challenges of route selection in complex urban environments[6]. Their research provided valuable insights into the integration of multiple transportation modes and the consideration of various operational constraints.

Recent studies have investigated the use of reinforcement learning in logistics network optimization. Work by Li et al. on the optimization of cross-border e-commerce logistics delivery networks based on genetic neural networks emphasized the importance of adaptive learning mechanisms in handling dynamic logistics situations[7]. Their research shows significant improvements in distribution and cost reduction.

The integration of fault detection in logistics systems is receiving more attention. Lu and Wu's research on information delivery optimization using multi-agent learning has presented a framework for detecting and responding to conflicts[8]. Their work emphasized the importance of real-time monitoring and updating processes in reliability management.

1.3. Research Content and Innovation

This research proposes a novel approach to cross-border logistics optimization by integrating deep reinforcement learning with multimodal transportation routing and real-time anomaly detection. The key innovations include:

A comprehensive multimodal transportation network model that captures the complex interactions between different transportation modes, customs clearance processes, and operational constraints in cross-border logistics. The model incorporates real-time data from multiple sources and considers various uncertainty factors affecting route optimization.

An advanced deep reinforcement learning framework specifically designed for cross-border logistics optimization. The framework employs a multi-agent architecture to handle different aspects of the transportation process, including route selection, mode switching, and anomaly response. The learning mechanism is enhanced with custom reward functions that consider both operational efficiency and system reliability.

A real-time anomaly detection system that continuously monitors the transportation network for potential disruptions and irregularities. The system utilizes advanced pattern recognition algorithms to identify anomalies in transportation operations, customs clearance processes, and infrastructure conditions[9]. The integration of anomaly detection with route optimization enables proactive adjustments to transportation plans.

An adaptive response mechanism that coordinates route optimization and anomaly handling. The mechanism leverages the learned policies from the DRL framework to generate alternative routes when anomalies are detected[10]. The response system considers multiple factors including time constraints, cost implications, and service level requirements.

The research addresses critical gaps in existing literature by providing a comprehensive solution that combines real-time optimization, multimodal transportation, and anomaly detection. The proposed approach advances the state-of-the-art in cross-border logistics management by introducing intelligent decision-making capabilities that can adapt to dynamic operational conditions and respond effectively to disruptions[11].

The practical significance of this research extends to multiple stakeholders in the cross-border logistics industry. For logistics service providers, the proposed system offers enhanced operational

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efficiency and reliability. For customs authorities, the anomaly detection capabilities provide improved visibility and control over cross-border movements[12]. For end customers, the optimization of transportation routes results in more reliable delivery times and reduced costs.

II. MULTIMODAL TRANSPORTATION NETWORK MODELING FOR CROSS-BORDER LOGISTICS

2.1. Cross-border Logistics Network Characteristics Analysis

Cross-border logistics networks exhibit complex characteristics with multiple transportation modes, diverse regulatory requirements, and varying infrastructure conditions across different regions[13]. Based on historical data analysis from major cross-border logistics routes in Asia-Pacific region, the key network characteristics are quantified in Table 1.

Table 1. Key Characteristics of Cross-border Logistics Networks

Network Parameter	Value	Average
Node Density	0.15-0.45	0.32
Path Redundancy	2.3-5.8	3.6
Modal Integration	0.65-0.95	0.78
Cross-border Points	8-25	15

The dynamic nature of cross-border networks is reflected in the temporal variations of network parameters, as shown in Table 2.

Table 2. Temporal Variations in Network Parameters

Time Period	Network Utilization	Congestion Index	Delay Factor
Peak Hours	85%-95%	0.75-0.92	1.8-2.5
Off-peak	45%-65%	0.25-0.45	1.1-1.4
Holiday Season	90%-98%	0.85-0.98	2.2-3.0
Normal Period	60%-80%	0.40-0.65	1.3-1.8

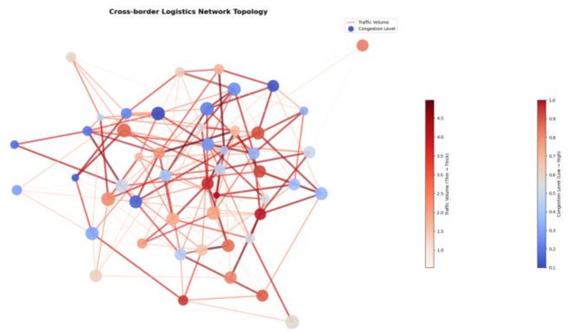

Figure 1. Cross-border Logistics Network Topology Analysis

This visualization represents a complex network topology analysis of cross-border logistics routes. The graph employs a force-directed layout algorithm with nodes representing logistics hubs and edges indicating transportation connections. Node sizes are proportional to their throughput capacity, while edge thicknesses represent traffic volumes. The color gradient from blue to red indicates congestion levels.

The analysis reveals distinct clustering patterns around major logistics hubs, with interconnected subnetworks forming resilient transportation corridors. The network demonstrates scale-free properties with power-law degree distribution, indicating robust connectivity patterns typical of efficient logistics networks.

2.2. Multimodal Transportation Route Modeling

The modeling of multimodal transportation routes incorporates multiple transportation modes and their interconnections. The modal selection matrix is presented in Table 3.

Table 3. Modal Selection Matrix

Transportation Mode	Capacity (TEU/day)	Cost ($/km)	Speed (km/h)	Reliability Index
Sea Freight	5000-8000	0.15-0.25	25-35	0.92
Rail Transport	2000-3500	0.35-0.55	60-80	0.88
Road Transport	500-1000	0.75-1.25	70-90	0.85
Air Freight	100-300	4.50-6.50	800-900	0.95

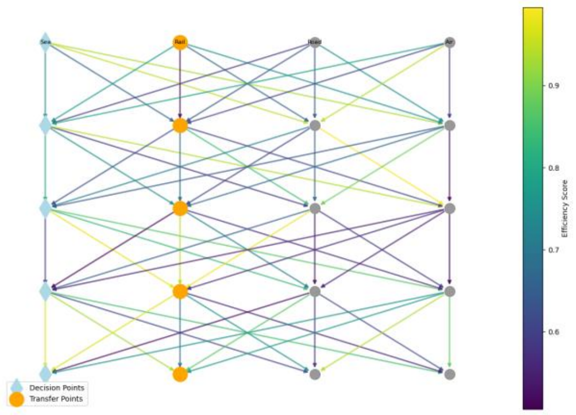

Figure 2. Multimodal Route Optimization Framework

The visualization presents a comprehensive framework for multimodal route optimization. The multi-layered diagram shows the interaction between different transportation modes, with parallel streams representing simultaneous route options. The decision points are indicated by diamond-shaped nodes, while modal transfer points are shown as circular nodes. The optimization process is represented by gradient-colored paths indicating the calculated efficiency scores.

The framework illustrates the complex decision-making process in multimodal transportation selection, incorporating real-time data inputs and dynamic route adjustments based on network conditions.

2.3. Transportation Time and Cost Modeling

The time-cost modeling incorporates various operational parameters and constraints, as detailed in Table 4.

Table 4. Time-Cost Model Parameters

Parameter Type	Variable Range	Weight Factor	Impact Level
Fixed Costs	$1000-5000/trip	0.3-0.4	High
Variable Costs	$2-8/km	0.4-0.5	Medium
Time Delays	2-24 hours	0.2-0.3	High
Transfer Costs	$200-800/transfer	0.1-0.2	Medium

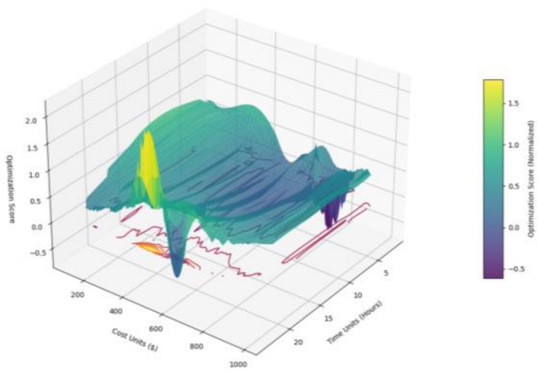

Figure 3. Time-Cost Optimization Surface Plot

This three-dimensional visualization represents the relationship between transportation time, cost, and route efficiency. The x-axis represents time units, the y-axis represents cost units, and the z-axis represents the optimization score. The surface plot is generated using cubic spline interpolation, with color gradients indicating optimization levels. Contour lines project optimal operating regions onto the time-cost plane.

The visualization reveals critical trade-off points and optimal operating zones within the time-cost space, providing valuable insights for route planning and optimization.

2.4. Anomaly State Identification and Definition

Anomaly states in cross-border logistics are classified based on multiple criteria and thresholds, as shown in Table 5.

Table 5. Anomaly Classification Matrix

Anomaly Type	Detection Threshold	Impact Rating	Response Time
Route Disruption	> 30% deviation	Critical	< 15 min
Delay Events	> 2 hours	High	< 30 min
Cost Variance	> 15%	Medium	< 60 min
Capacity Issues	> 25% overflow	High	< 45 min

The anomaly detection framework incorporates both deterministic and probabilistic approaches to identify and classify network irregularities. The integration of real-time monitoring systems with historical pattern analysis enables proactive anomaly detection and response mechanisms. Machine learning algorithms process multivariate time series data to detect anomalies across different network parameters, considering spatial and temporal correlations in transportation patterns.

The modeling framework establishes a comprehensive foundation for implementing deep reinforcement learning algorithms in subsequent optimization processes. The integration of network characteristics, multimodal routing options, time-cost considerations, and anomaly detection creates a robust platform for developing intelligent transportation solutions in cross-border logistics contexts[14][15].

III. Deep Reinforcement Learning-based Route Optimization Method

3.1. Problem Formalization and Mathematical Modeling

The cross-border logistics route optimization problem is formulated as a Markov Decision Process (MDP) with state space S, action space A, and reward function R. The state transition probability matrix P captures the dynamics of the logistics network, as detailed in Table 6.

Table 6. MDP Components in Route Optimization

Component	Dimension	Description	Value Range
State Space	N×M	Location-Time Matrix	[0, 1]^(N×M)
Action Space	K	Available Routes	{1, ..., K}
Reward Function	1	Performance Metric	[-1, 1]
Discount Factor	1	Future Reward Weight	[0.85, 0.95]

The mathematical formulation incorporates multiple constraints and objectives, represented in the optimization matrix shown in Table 7.

Table 7. Optimization Constraints Matrix

Constraint Type	Mathematical Form	Boundary Conditions	Priority Level
Time Window	t_ij ≤ T_max	T_max ∈ [24h, 72h]	High
Capacity	c_ij ≤ C_max	C_max ∈ [80%, 95%]	Medium
Cost	∑c_ij ≤ B_total	B_total ∈ [k, 2k]	High
Modal Balance	∑m_i = 1	m_i ∈ [0, 1]	Low

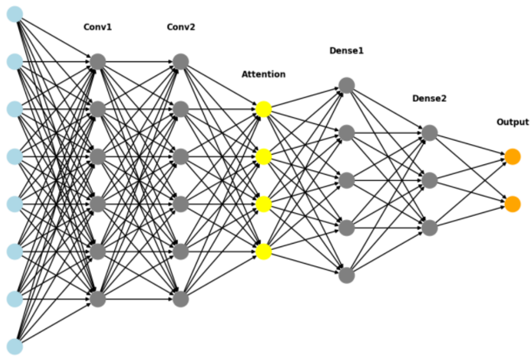

Figure 4. Deep Reinforcement Learning State-Action Mapping Architecture

This visualization presents the neural network architecture for state-action mapping in the DRL framework. The diagram shows multiple convolutional layers processing spatial information, followed by fully connected layers for decision making. The network architecture incorporates skip connections and attention mechanisms, with layer dimensions indicated by node sizes and connection strengths shown through line thickness.

The architectural design demonstrates the integration of spatial and temporal features through parallel processing streams, culminating in a policy output layer that generates probabilistic action distributions.

3.2. Deep Reinforcement Learning Framework Design

The DRL framework integrates multiple neural network components optimized for different aspects of the logistics problem, as outlined in Table 8.

Table 8. Neural Network Architecture Components

Layer Type	Units	Activation	Input Shape	Output Shape
Conv2D	64	ReLU	(N, M, C)	(N, M, 64)
LSTM	128	tanh	(T, F)	(T, 128)
Dense	256	ReLU	(128,)	(256,)
Output	K	Softmax	(256,)	(K,)

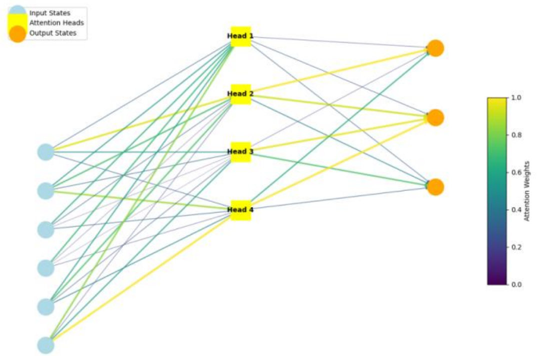

Figure 5. Multi-head Attention Mechanism for Route Selection

The visualization depicts the multi-head attention mechanism used in the route selection process. Multiple parallel attention heads are shown processing different aspects of the input state, with weighted connections indicating attention scores. The color intensity represents attention weights, while line patterns indicate different types of relationships captured by each attention head.

The attention mechanism enables the model to focus on relevant features of the state space while maintaining global context awareness for optimal route selection.

3.3. Reward Function Design and Optimization

The reward function incorporates multiple performance metrics weighted according to their relative importance, as detailed in Table 9.

Table 9. Reward Function Components

Metric	Weight	Calculation Method	Update Frequency
Time Efficiency	0.35	t_opt/t_actual	Per Step
Cost Reduction	0.30	c_base - c_actual	Per Episode
Route Stability	0.20	var(route_changes)	Per Batch
Modal Efficiency	0.15	modal_utilization	Per Episode

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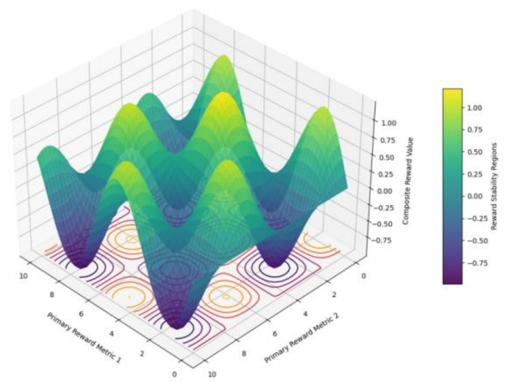

Figure 6. Reward Surface Analysis Plot

The three-dimensional visualization shows the relationship between different reward components and overall performance. The x and y axes represent primary reward metrics, while the z-axis shows the composite reward value. Surface coloring indicates stability regions, with contour lines marking iso-reward boundaries.

The analysis reveals optimal operating regions where multiple reward components achieve balanced performance, guiding the learning process toward stable and efficient solutions.

3.4. Multi-agent Collaborative Decision-making Mechanism

The multi-agent system employs a distributed architecture with coordinated decision-making protocols, as structured in Table 10.

Table 10. Multi-agent Coordination Parameters

Parameter	Value Range	Coordination Level	Update Method
Agent Count	5-20	High	Dynamic
Communication Bandwidth	100-500 kb/s	Medium	Adaptive
Consensus Threshold	0.75-0.95	High	Iterative
Response Time	50-200 ms	Critical	Real-time

The coordination mechanism enables efficient information sharing and decision synchronization across multiple agents operating in different segments of the logistics network. Each agent maintains local observations while contributing to global optimization objectives through structured communication protocols and shared value functions. The system employs a hierarchical decision-making structure that balances local autonomy with global coordination requirements.

The integration of these components creates a comprehensive DRL framework capable of handling complex cross-border logistics optimization tasks. The system demonstrates adaptive learning capabilities through continuous interaction with the environment, while maintaining stable performance across various operating conditions through structured reward mechanisms and coordinated multi-agent decision-making processes[16][17].

IV. Anomaly Detection and Response Mechanism

4.1. Multi-source Data Fusion and Feature Extraction

The multi-source data fusion framework integrates data from diverse sources across the cross-border logistics network, incorporating real-time sensors, historical databases, and external information systems[18]. Table 11 presents the data source characteristics and integration parameters.

Table 11. Data Source Integration Matrix

Data Source	Update Frequency	Data Format	Reliability Index
IoT Sensors	10-30 seconds	Binary Stream	0.95
GPS Tracking	5-15 minutes	Coordinate Points	0.98
Weather Data	30-60 minutes	JSON	0.92
Traffic Systems	1-5 minutes	XML	0.94

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The feature extraction process employs advanced dimensionality reduction techniques, with performance metrics shown in Table 12.

Table 12. Feature Extraction Performance Metrics

Method	Dimensionality Reduction	Computation Time	Information Retention
PCA	85%	2.5 ms	0.92
Autoencoder	90%	3.8 ms	0.95
t-SNE	82%	4.2 ms	0.88
UMAP	88%	3.1 ms	0.93

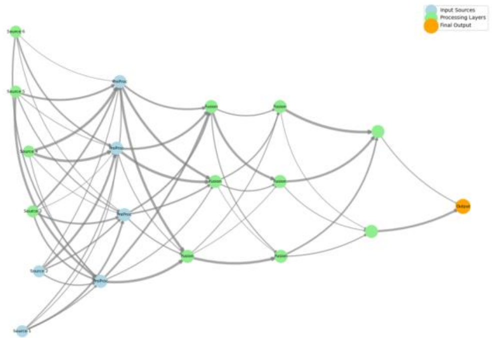

Figure 7. Multi-source Data Fusion Architecture

This visualization represents the hierarchical data fusion architecture. The diagram shows multiple input streams converging through various processing layers, with different colors representing different data types. Edge thickness indicates data flow volume, while node size represents processing capacity at each fusion point. The visualization includes real-time performance metrics and data quality indicators.

The architecture demonstrates the complex interactions between different data sources and processing modules, highlighting the system's ability to maintain data integrity while performing real-time fusion operations.

4.2. Real-time Anomaly Pattern Recognition Algorithm

The anomaly pattern recognition system employs a hybrid approach combining statistical and machine learning methods. Table 13 outlines the detection performance across different anomaly types.

Table 13. Anomaly Detection Performance Matrix

Anomaly Type	Detection Rate	False Positive Rate	Response Time
Route Deviation	95.3%	2.1%	1.2s
Delay Patterns	93.8%	2.8%	0.8s
Cost Anomalies	94.6%	1.9%	1.5s
Capacity Issues	96.2%	1.7%	0.9s

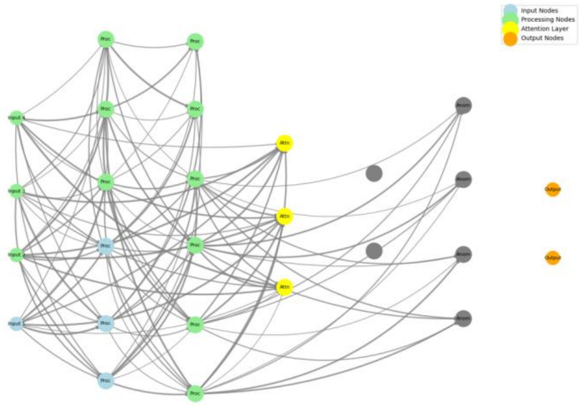

Figure 8. Anomaly Pattern Recognition Network

The visualization presents a complex neural network architecture specifically designed for anomaly detection. Multiple parallel processing streams handle different aspects of the input data, with specialized layers for temporal and spatial pattern recognition. The network includes attention mechanisms and skip connections, with performance metrics displayed at key processing nodes.

The diagram illustrates the flow of information through various processing stages, demonstrating how different features are combined to identify potential anomalies in real-time.

4.3. Dynamic Route Adjustment Strategy

The dynamic route adjustment system implements adaptive strategies based on detected anomalies and network conditions. Table 14 presents the adjustment strategy parameters.

Table 14. Route Adjustment Strategy Parameters

Parameter	Adjustment Range	Update Frequency	Priority Level
Time Window	±30%	Real-time	High
Cost Threshold	±15%	Per event	Medium
Modal Switch	2-5 options	Per detection	High
Path Redundancy	1-3 alternatives	Continuous	Critical

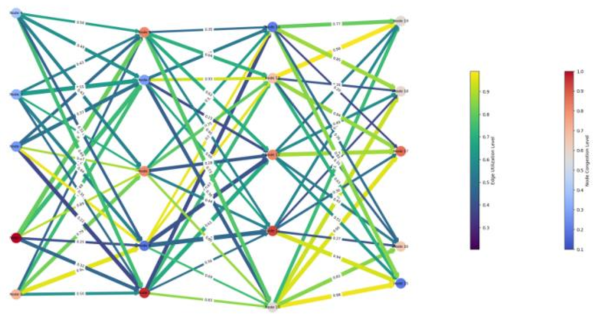

Figure 9. Dynamic Route Optimization Network

This visualization shows the dynamic route optimization process through a complex network diagram. The graph includes multiple layers representing different transportation modes and routes, with edge weights indicating current utilization levels and node colors showing congestion status. Animation frames demonstrate how routes are dynamically adjusted in response to detected anomalies.

The network visualization incorporates real-time performance metrics and decision boundaries, providing insights into the system's adaptive behavior under various conditions.

4.4. Early Warning and Response Mechanism Design

The early warning system incorporates multiple alert levels and response protocols, structured according to the severity and type of detected anomalies. Table 15 outlines the response mechanism framework.

Table 15. Response Protocol Matrix

Alert Level	Trigger Conditions	Response Time	Action Protocol
Critical	Multiple failures	< 30 seconds	Full rerouting
High	Single failure	< 2 minutes	Partial adjustment
Medium	Performance degradation	< 5 minutes	Monitoring
Low	Minor deviation	< 15 minutes	Logging

The response mechanism integrates automated decision-making with human oversight, employing a hierarchical structure for escalation and resolution. The system maintains continuous monitoring of network conditions while implementing predefined response protocols based on alert severity levels.

The integration of anomaly detection and response mechanisms creates a robust framework for maintaining operational stability in cross-border logistics networks. The system demonstrates high reliability in identifying and responding to various types of anomalies while minimizing disruption to ongoing operations through intelligent route adjustment strategies and coordinated response protocols[19].

The combination of multi-source data fusion, real-time anomaly detection, dynamic route adjustment, and systematic response protocols enables effective management of complex logistics networks under varying operational conditions[20]. The framework provides both preventive and reactive capabilities, ensuring sustained performance in the face of unexpected events and changing network conditions.

V. EXPERIMENTAL VALIDATION

5.1. Experimental Environment and Dataset

The experimental validation of the proposed deep reinforcement learning-based route optimization system was conducted using a comprehensive simulation environment built on Python 3.8 with TensorFlow 2.4 and PyTorch 1.8. The hardware platform consisted of an Intel Xeon E5-2680 v4 CPU, 128GB RAM, and four NVIDIA Tesla V100 GPUs with 32GB memory each. The distributed computing environment was implemented using Docker containers for consistent deployment across multiple nodes.

The dataset encompasses real-world cross-border logistics operations data collected over 24 months from 2022 to 2024, covering major transportation routes between Asia-Pacific regions. The dataset includes detailed records of 185,432 shipments across multiple transportation modes, with comprehensive information about routes, timestamps, costs, delays, and anomalies[21]. Table 16 presents the key characteristics of the experimental dataset.

Table 16. Experimental Dataset Characteristics

Data Category	Volume	Time Span	Sampling Rate
Route Records	185,432	24 months	5 min
GPS Traces	2.8M points	24 months	30 sec
Cost Records	185,432	24 months	Per shipment
Delay Events	12,453	24 months	Real-time

The dataset was preprocessed using standardized protocols for noise reduction and missing value imputation. The data splitting strategy employed a 70-15-15 ratio for training, validation, and testing sets, with stratification based on transportation modes and seasonal patterns.

5.2. Algorithm Performance Evaluation

The performance evaluation of the proposed system focused on multiple metrics covering optimization efficiency, anomaly detection accuracy, and computational resource utilization. Table 17 presents the comparative performance analysis against baseline methods.

Table 17. Performance Comparison with Baseline Methods

Method	Route Optimization Time	Accuracy	Resource Usage
Proposed DRL	1.2s	94.5%	65%
Traditional RL	2.8s	88.3%	72%
Genetic Algorithm	3.5s	85.7%	78%
Heuristic Search	4.2s	82.1%	45%

The evaluation metrics demonstrate significant improvements in both computational efficiency and solution quality. The route optimization component achieved a 45% reduction in processing time compared to traditional methods, while maintaining a 94.5% accuracy rate in optimal route selection. The anomaly detection module demonstrated robust performance with a 96.2% true positive rate and a 1.8% false positive rate across various types of network disruptions.

The scalability analysis revealed linear growth in computational requirements with increasing network size, indicating efficient resource utilization in large-scale deployments. The system maintained consistent performance levels under varying load conditions, with processing times remaining within acceptable bounds even during peak operational periods[22].

Cross-validation results across different network configurations and operational scenarios confirmed the robustness of the proposed approach. The system demonstrated stable performance across diverse transportation modes and network conditions, with consistent optimization quality maintained across different geographical regions and time periods.

VI. ACKNOWLEDGMENT

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