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Design and Implementation of Regional Logistics Resource Intelligent Matching and Supply Chain Integration Control System Based on Multi-Source Data Fusion

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Abstract

Regional logistics serves as a critical pillar supporting the efficient circulation of industrial and supply chains. Aiming at prominent challenges in current regional logistics, including fragmented multi-source data, severe resource mismatches, and static & rigid scheduling modes, traditional approaches fail to cope with complex logistics scenarios compounded by order fluctuations, traffic disruptions and meteorological disturbances. This paper constructs a hierarchical fusion framework for multi-source heterogeneous regional logistics data, integrating Internet of Things (IoT) perception data, order data, geographic transportation data, meteorological data and supply chain ledger data. An entropy weight-attention improved fusion model is adopted to realize accurate feature reconstruction for logistics data with high noise and missing values.

On this basis, a multi-constraint mathematical model for logistics resource supply-demand matching is established, and an improved Proximal Policy Optimization (PPO) reinforcement learning matching algorithm is designed. A multi-objective reward function balancing cost, timeliness, resource utilization rate and carbon emissions is constructed to complete dynamic intelligent matching of transportation capacity, warehousing and distribution nodes. Meanwhile, a closed-loop management and control mechanism of "Perception-Matching-Scheduling-Execution-Feedback" is built, and a regional logistics intelligent control system is developed based on cloud-edge collaboration. Simulation experiments are carried out using real logistics data of a domestic metropolitan area from 2024 to 2025. The results show that compared with traditional algorithms, the proposed method improves matching accuracy by 12.47%, reduces resource idle rate by 9.62%, shortens supply chain turnover time by 14.13%, and achieves excellent robustness under order peak and sudden disturbance scenarios. This research provides effective theoretical models and engineering practical schemes for integrated management & control of regional smart logistics and flexible coordination of supply chains. (Sun X & Wang H., 2025)

Keywords: multi-source data fusion, regional logistics resources, intelligent matching, supply chain integration, closed-loop control, improved PPO algorithm, cloud-edge collaboration, multi-objective optimization, smart logistics, disturbance adaptability, resource pooling, logistics scheduling, IoT perception, low-carbon logistics

1. Introduction

1.1 Research Background and Problem Statement

Current logistics systems face obvious practical drawbacks. Up to 18% of multi-source heterogeneous logistics data contains missing values and noise, causing matching and decision errors. Conventional static open-loop optimization algorithms poorly adapt to dynamic changes like order surges and traffic fluctuations. Slow information exchange between supply chain parties leads to 43% of supply chain interruptions, as existing platforms lack closed-loop adjustment and robust intelligent scheduling support. To tackle these industrial pain points, this paper studies multi-source data fusion-based regional logistics intelligent matching and supply chain integrated closed-loop control, with solid theoretical and practical engineering value.

1.2 Review of Domestic and Foreign Research Status

Traditional three-tier logistics data fusion algorithms show unstable performance, with 18%–24% feature distortion amid faulty data and offline systems, and cannot fit multi-stakeholder regional logistics scenarios. Classic optimization algorithms easily get trapped in local optima under massive dynamic orders; mainstream deep reinforcement learning schedulers only optimize single metrics (cost or timeliness), ignoring multi-dimensional limits such as warehouse capacity and carbon emissions.

Most supply chain integration research focuses on internal coordination of single firms, with few studies on cross-enterprise closed-loop regional logistics control. Existing smart logistics platforms merely visualize basic workflows without full "Perception-Decision-Execution-Feedback" closed loops, unable to quickly respond to market shocks. While cloud-edge collaboration frameworks are widely adopted, a unified solution combining data fusion, intelligent matching and closed-loop control is still absent. This paper addresses the three core research gaps summarized above.

1.3 Research Content and Scientific Questions

Three key scientific questions are explored:

1) How to clean, align and hierarchically fuse multi-source heterogeneous logistics data (IoT records, business forms, spatiotemporal weather data) to reduce bias from noise and missing data;
2) How to build a dynamic intelligent matching model under cost, timeliness, load and carbon emission constraints to optimize regional logistics supply-demand allocation;
3) How to design a supply chain closed-loop integrated control mechanism and develop a verifiable cloud-edge collaborative intelligent control system.

Main research work: build a regional logistics multi-source data system and an entropy weight-attention hierarchical fusion model; construct a logistics resource matching mathematical model and an enhanced multi-objective PPO matching algorithm; establish supply chain closed-loop collaborative control logic; fully develop the control system; validate the model via ablation tests and real-data multi-scenario comparisons.

1.4 Research Innovations

1) **Model Innovation**: Propose an entropy weight-attention hierarchical multi-source data fusion model. Dynamic weighting across data-feature-decision layers improves heterogeneous time-series data fusion and suppresses noise interference for downstream decisions.
2) **Algorithm Innovation**: Optimize PPO reinforcement learning for multi-constraint logistics scenarios. A multi-objective reward function balances cost, timeliness, resource utilization and carbon emissions to boost matching stability amid dynamic disruptions.
3) **Mechanism Innovation**: Put forward a full "Perception-Matching-Scheduling-Execution-Feedback" supply chain closed-loop control framework, enabling disturbance recognition and adaptive rescheduling to overcome open-loop scheduling's slow emergency response.
4) **Engineering Innovation**: Fully deploy all algorithms into a modular cloud-edge collaborative control system with encapsulated fusion, matching and closed-loop control modules, realizing the conversion of theoretical models into usable commercial logistics platforms.

2. Relevant Theories and Key Technical Foundations

2.1 Regional Logistics Resources and Supply Chain Coordination Theory

Regional logistics resources are divided into supply set S and demand set D.

Supply set: $S=S_1,S_2,...,S_m$, covering transportation capacity, warehousing bays, transit nodes and loading/unloading equipment;

Demand set: $D=D_1,D_2,...,D_n$, representing logistics orders to be executed within the region, with each order containing attributes such as origin, destination, cargo weight, time window and commodity category.

Supply chain integration is split into horizontal integration and vertical integration. Horizontal integration refers to overall scheduling of homogeneous logistics resources, e.g., pooled management of transport vehicles and warehousing nodes across multiple enterprises. Vertical integration connects the full business chain covering order issuance, warehouse picking, trunk transportation, terminal distribution and information feedback. Robust closed-loop control theory emphasizes continuous collection of external system state information and feedback of execution results to decision-making units, which automatically revise decision outputs when system states deviate from expected targets. This idea can be migrated to the dynamic scheduling scenario of regional logistics supply chains. (Lu Y., 2025)

2.2 Basic Theory of Multi-Source Heterogeneous Data Fusion

Three foundational levels of data fusion are defined as follows:

1) Data-level Fusion: Registration and merging at the raw data level, retaining original detailed information with high requirements on data integrity;
2) Feature-level Fusion: Extracting feature vectors from different data sources to complete feature transformation, screening and fusion, serving as the core processing layer for heterogeneous data;
3) Decision-level Fusion: Receiving local decision outputs from multiple subsystems to complete comprehensive judgment of global decisions.

Assume there are k groups of heterogeneous data sources, with feature vector x_i $(i=1,2,...,k)$ extracted from each source, and the fused output feature vector denoted as $\boldsymbol{X}$. The fusion process can be abstracted as: $\boldsymbol{X}=F(x_1,x_2,...,x_k,\boldsymbol{W})$.

Where $F(\cdot)$ denotes the fusion mapping function, and $\boldsymbol{W}$ represents the weight matrix corresponding to each data source. Traditional fixed-weight methods treat $\boldsymbol{W}$ as a constant matrix, while this paper introduces entropy weight and attention mechanism to enable dynamic adjustment of the weight matrix with samples.

2.3 Multi-Objective Optimization and Reinforcement Learning Fundamentals

The mathematical formulation of multi-objective optimization problems is as follows:

Where z represents decision variables; $f_1,...,f_p$ stand for multiple optimization objectives; g_i and h_j are inequality and equality constraints respectively. Multi-objective optimization generally has no unique global optimal solution, and a Pareto optimal solution set is obtained, from which a compromised optimal scheme is selected according to business preferences.

PPO (Proximal Policy Optimization) is a policy gradient reinforcement learning algorithm that avoids severe oscillation of policy updates by limiting the gap between old and new policies. Its objective function is defined as:

$$L^{CLIP}(\theta)=\mathrm{E}_t\left[min\left(r_t(\theta)A_t,\mathrm{clip}(r_t(\theta),1\text{-}\epsilon,1+\epsilon)A_t\right)\right]$$

$$r_t(\theta)=\frac{\pi_\theta(a_t\mid s_t)}{\pi_{\theta_{\mathrm{old}}}(a_t\mid s_t)}$$

Where $r_t(\theta)$ denotes the policy ratio, A_t is the advantage function, and ϵ represents the clipping hyperparameter. On the basis of vanilla PPO, this paper adds an attention layer to weight and filter state features, adapting to the high-dimensional state space of logistics.

2.4 Technical Foundations of Cloud-Edge Collaborative Systems

The cloud-edge collaborative architecture splits computing tasks between edge nodes and cloud servers. Edge nodes locally complete collection, preliminary cleaning and lightweight inference of on-site IoT data to reduce network bandwidth pressure; the cloud undertakes global multi-source data fusion, large-scale model inference of reinforcement learning and global supply chain decision-making. Edge nodes and the cloud exchange data via message queues, realizing a distributed operation mode of "local lightweight processing at edges, global optimization on the cloud".

3. Analysis of Multi-Source Data Features and Construction of Hierarchical Fusion Model for Regional Logistics

3.1 Multi-Source Data System and Feature Statistics of Regional Logistics

The dataset adopted in this paper originates from real business libraries of regional logistics in a metropolitan area during 2024–2025, covering five categories of data sources. The statistical overview is shown in Table 1.

Table 1. Statistical Summary of Multi-Source Regional Logistics Data Composition

Data Category	Data Content	Data Type	Sample Volume	Missing Rate	Noise Ratio
IoT Perception Data	Vehicle GPS, warehouse temperature & humidity, equipment status	Time-series numerical data	486,200	11.36%	7.82%
Order Transaction Data	Order ID, cargo volume, origin & destination, time window	Structured business data	217,400	4.25%	2.17%
GIS Geospatial Data	Node coordinates, road network distance, road grade	Spatial vector data	3,260	0	0
Traffic-Meteorological Time-Series Data	Road section traffic speed, precipitation, wind force, temperature	Time-series numerical data	134,800	8.71%	4.43%
Supply Chain Ledger Data	Enterprise inventory, warehouse occupancy, historical performance records	Structured business data	89,300	6.54%	3.26%

It can be observed from Table 1 that IoT perception and traffic-meteorological time-series data feature significantly higher missing and noise ratios than business ledger data. Different data sources differ drastically in dimension and sampling frequency, forming a typical multi-source heterogeneous dataset. Major data challenges include time-series segment missing caused by temporary sensor disconnection, abnormal coordinate points from GPS drift, inconsistent coding standards across business systems, and unsynchronized alignment of temporal-spatial dimensions. (Wang X, Chen L & Zhang Y., 2023)

3.2 Preprocessing Workflow for Multi-Source Data

Preprocessing is divided into three steps: data cleaning, standardization and spatio-temporal alignment.

1) Data Cleaning: The 3σ criterion is adopted to identify numerical outliers; linear interpolation combined with adjacent historical segments is used for adaptive filling of time-series missing values; business fields with missing entries are marked as invalid samples or supplemented based on historical homogeneous samples per business rules. Duplicate records are deduplicated.

2) Data Standardization: Numerical features are mapped to the interval [0,1] via min-max normalization:

$$x^* = \frac{x - x_{min}}{x_{max} - x_{min}}$$

Categorical text features are converted via one-hot encoding; geographic coordinates are uniformly converted to the WGS-84 coordinate system.

3) Spatio-Temporal Alignment: All data are aligned to 5-minute time slices, and a unified spatial reference benchmark is adopted for all logistics nodes and vehicle positions, realizing temporal and spatial alignment of data from diverse sources.

3.3 Entropy Weight-Attention Improved Hierarchical Data Fusion Model

This paper adopts a three-layer fusion architecture consisting of data level, feature level and decision level.

1) Data-level Fusion Layer: Completes

cleaning and spatio-temporal alignment of raw time-series data, outputting standardized preprocessed raw datasets without in-depth feature transformation.

2) Feature-level Fusion Layer (Core Module): Basic feature sets are first extracted from each category of data sources, and the entropy weight method is used to calculate objective weights for each data source. The entropy calculation formula is:

$$E_j=-\frac{1}{\ln n}\sum_{i=1}^{n} p_{ij}\ln p_{ij}$$

Where E_j denotes the entropy value of the j-th feature, and p_{ij} represents the probability of feature values. A smaller entropy value indicates higher information content of the feature. Initial objective weights are derived from entropy values. Subsequently, self-attention mechanism is introduced to dynamically reweight internal sub-dimensions of different features, capturing internal correlations among features and outputting fused high-dimensional comprehensive feature vectors.

3) Decision-level Fusion Layer: Receives output vectors from the feature layer as well as local judgment results of partial business subsystems to complete high-level decision fusion, outputting supply resource state vectors and demand order state vectors directly for the upper matching model.

The overall input of the fusion model is five categories of preprocessed multi-source data, and the output is a standardized state feature matrix of the regional logistics system.

3.4 Evaluation and Comparison of Fusion Models

Three indicators including feature integrity, feature redundancy and time-series consistency are selected to evaluate fusion performance. The proposed model is compared with Kalman filter fusion, simple weighted fusion and D-S evidence fusion, with results presented in Table 2.

Table 2. Performance Comparison of Different Data Fusion Models

Fusion Model	**Feature Integrity /%**	**Feature Redundancy /%**	**Time-Series Consistency /%**
Kalman Filter Fusion	82.31	18.74	83.62
Simple Weighted Fusion	78.65	22.16	79.47
D-S Evidence Fusion	84.27	16.39	84.80
Proposed Entropy Weight-Attention Hierarchical Fusion	91.53	9.28	92.46

Results in Table 2 demonstrate that the proposed hierarchical fusion model outperforms comparative methods significantly in feature integrity and time-series consistency, while effectively reducing feature redundancy. After fusion processing, feature distortion caused by raw data noise and missing values is drastically suppressed, providing high-quality input for subsequent resource matching algorithms.

4. Intelligent Matching Model of Logistics Resources Based on Multi-Source Fusion Features

4.1 Mathematical Description and Constraints of Resource Matching Problem

After outputting system states via the fusion model, resource matching essentially allocates demand order set D to supply resource set S under multiple constraints. A 0-1 decision variable z_{ij} is defined as:

Constraints:

1) Capacity & warehousing constraint: Total cargo volume of orders undertaken by resource S_j shall not exceed the rated load upper limit;

2) Time window constraint: Orders must be received and delivered within the specified time window;

3) Spatial reachability constraint: Resources can cover the geographic service scope of orders;

4) Hard business constraint: Restrictions on matching hazardous goods and special cargo with corresponding transport resources.

Four optimization objectives are defined:

minimization of comprehensive logistics cost, minimization of total order delivery duration, minimization of resource idle rate, and minimization of carbon emissions. This constitutes a typical multi-constraint and multi-objective combinatorial optimization problem.

4.2 Design of Improved PPO Intelligent Matching Algorithm

The state space s_t of reinforcement learning is constructed from fusion features output in Chapter 3, with state vectors containing order demand features, vehicle & warehousing supply states, traffic and meteorological environmental features. The action space a_t represents allocation actions between orders and resources.

A multi-objective composite reward function R_t is designed as follows:

$$R_t=\omega_1 R_{\text{cost}}+\omega_2 R_{\text{time}}+\omega_3 R_{\text{util}}+\omega_4 R_{\text{carbon}}+R_{\text{penalty}}$$

Where R_{cost} = cost reward term, R_{time} = timeliness reward term, R_{util} = resource utilization reward term, R_{carbon} = carbon emission reward term, R_{penalty} = penalty term for constraint violation (negative reward imposed once hard constraints of load and time window are violated); $\omega_1,\omega_2,\omega_3,\omega_4$ denote weights of each term.

An attention layer is added before the PPO policy network to automatically assign attention weights to high-dimensional state features, strengthening focus on key features such as order time windows and load limits while lowering interference from irrelevant features. During model training, experience replay is adopted to collect samples and clipped policy updates are executed; during online inference, real-time fusion features are received to output optimal order-resource matching schemes. An incremental learning mechanism is configured: when drastic state shifts occur in the regional logistics system, the model can complete iterative updates with small samples without full retraining.

4.3 Experiment and Result Analysis of Matching Model

Experimental Environment: Python3.9, PyTorch1.13; Hardware: Intel Xeon 8375C CPU, 24GB video memory. Comparative algorithms include PSO particle swarm optimization, vanilla PPO and static weighted matching (Liu S, Li J & Han Y., 2024). Evaluation indicators: matching accuracy, average resource idle rate, average completion duration per batch of orders. Two test scenarios (normal operation and order peak) are set, and experimental results are shown in Table 3.

Table 3. Test Result Comparison of Different Matching Algorithms

Algorithm	Scenario	Matching Accuracy (%)	Average Resource Idle Rate (%)	Average Order Completion Duration /h
PSO Particle Swarm Optimization	Normal Operation	81.26	18.41	11.72
PSO Particle Swarm Optimization	Order Peak	72.53	23.68	16.35
Vanilla PPO	Normal Operation	86.74	14.75	9.86
Vanilla PPO	Order Peak	78.31	18.94	13.27
Proposed Improved PPO	Normal Operation	93.73	8.79	8.14
Proposed Improved PPO	Order Peak	85.00	12.32	10.69

It can be seen from Table 3 that the proposed improved PPO algorithm outperforms comparative algorithms comprehensively under both normal and order peak scenarios. Compared with PSO, matching accuracy rises by 12.47% and resource idle rate drops by 9.62% under normal scenarios, and favorable performance is maintained during order peaks, verifying the algorithm's capacity to cope with business volume fluctuations.

Further ablation experiments are conducted to verify the contribution of two innovative modules: attention layer and multi-objective composite reward function, as shown in Table 4.

Table 4. Ablation Experiments of Matching Model

Model Configuration	**Matching Accuracy (%)**	**Resource Idle Rate (%)**
Remove Attention Layer + Single-Objective Reward	82.45	17.20
Add Attention Layer + Single-Objective Reward	86.81	14.63
No Attention Layer + Multi-Objective Reward	88.24	12.97
Full Model (Attention Layer + Multi-Objective Reward)	93.73	8.79

Ablation results prove that both attention feature screening mechanism and multi-objective composite reward function positively boost model performance, and optimal performance is achieved when the two modules are deployed simultaneously.

5. Closed-Loop Collaborative Control Mechanism for Supply Chain Integration

5.1 Analysis of Fragmentation Problems in Regional Supply Chains

Regional logistics supply chains involve multiple participants including cargo owners, third-party logistics providers, warehousing parks, transport fleets and terminal delivery teams. In traditional operation modes, matching results are directly issued for execution without continuous collection and feedback of execution status. When disruptions such as road congestion, vehicle breakdowns and temporary order changes emerge, the system cannot trigger automatic rescheduling and requires manual intervention, leading to delivery delays and resource waste. Disturbances are categorized into three types:

- Periodic disturbances: e.g., morning and evening rush hour traffic congestion;
- Random sudden disturbances: vehicle breakdowns, extreme weather;
- Business disturbances: sharp surge in order volume, revision of order information.

5.2 Multi-Level Architecture for Supply Chain Integration

Supply chain integration is realized from three levels:

1) Resource Layer Integration: A dynamic global resource ledger is obtained via multi-source fusion, with scattered transportation capacity and warehousing nodes affiliated to different enterprises managed logically in a pooled manner to form a unified global resource status view;
2) Business Chain Layer Integration: The full business link covering order receiving, warehouse picking, resource matching, transport scheduling, delivery signing and result feedback is connected to eliminate information gaps between links;
3) Multi-Participant Coordination Layer Integration: Standardized information interaction interfaces are established to realize mutual access to status information among cargo owners, logistics service providers and warehousing nodes.

5.3 Operation Mechanism of Closed-Loop Collaborative Control

This paper constructs a closed-loop control logic of "Perception-Matching-Scheduling-Execution-Feedback-Re-Decision".

1) Perception Link: Continuous collection of IoT and business system data, which is sent to the multi-source data fusion module to update the global system state in real time;
2) Matching Link: Call the improved PPO model in Chapter 4 to output resource matching schemes;
3) Scheduling Issuance Link: Convert matching schemes into specific operation instructions and issue them to vehicle and warehouse terminals;
4) Execution Monitoring Link: Persistent collection of on-site execution status;
5) Disturbance Identification & Feedback Link:

Disturbance discrimination thresholds are set to compare deviations between actual execution status and planned status. Disturbances are confirmed when deviations exceed thresholds;

6) Re-Decision Link: Trigger recalculation of the model to generate adjusted matching & scheduling schemes, realizing closed-loop adaptive regulation.

The abstract expression of closed-loop control logic is:

Where X_t = fused system state at time t; $M(\cdot)$ = intelligent matching mapping function; Y_t = output scheduling scheme; $E(Y_t)$ = execution feedback information; ξ_t = external random disturbance; $F(\cdot)$ = fusion update function. Execution feedback and external disturbances jointly participate in the update of system states at the next time step to realize closed-loop iteration.

5.4 Simulation Verification of Closed-Loop Control Mechanism

A sudden vehicle breakdown disturbance scenario is set for simulation: partial transport capacity fails randomly at simulation time step 120 (Chen H, Wang Q & Zhao K., 2025). Traditional open-loop scheduling (no adjustment after matching output) and the proposed closed-loop control mechanism are compared on supply chain operation indicators, as shown in Table 5.

Table 5. Comparison Between Closed-Loop and Open-Loop Modes Under Sudden Disturbance Scenarios

Operation Mode	**Order Fulfillment Rate (%)**	**Average Delay Duration /h**	**Resource Reallocation Response Time /s**
Traditional Open-Loop Scheduling	74.18	3.86	—
Proposed Closed-Loop Collaborative Control	90.52	1.41	2.86

Under the disturbance of sudden transport capacity failure, the closed-loop control mechanism can rapidly identify abnormalities and complete resource reallocation, greatly lifting the order fulfillment rate. This verifies that the closed-loop integrated control mechanism effectively enhances the supply chain's adaptability to sudden disturbances.

6. Overall Design and Engineering Implementation of Intelligent Control System

6.1 System Design Objectives and Principles Objectives

Support multi-source logistics data access & layered fusion, regional logistics intelligent matching, supply chain closed-loop collaborative scheduling, visual operation panels, and stable high-concurrency operation under disturbances.

Principles

Hierarchical modular decoupling, cloud-edge distributed computing, algorithm-business separation, extensible interfaces for iteration, data access security and permission isolation.

6.2 Four-Layer System Architecture

The system consists of Perception Access, Data Fusion Governance, Intelligent Decision and Business Application Layers.

1) Perception Access Layer: Collect IoT, GIS, business, meteorology and traffic data; edge nodes preprocess raw data and forward standardized data to cloud via message queues.

2) Data Fusion Governance Layer: Integrate data cleaning, spatio-temporal alignment, entropy weight-attention fusion and distributed storage modules to generate fused features for upper decision-making.

3) Intelligent Decision Layer (Core): Wrap improved PPO matching, disturbance identification and closed-loop control modules. It outputs matching schemes and scheduling instructions via API services.

4) Business Application Layer: Visual dashboard covers resource monitoring, order management, matching scheme display, supply chain tracking, abnormal alerts, statistics and user rights management.

Backend adopts SpringBoot microservices; InfluxDB stores IoT time-series data and MySQL for business orders. Frontend is Vue-based; reinforcement learning models are deployed as inference services.

6.3 Core Module Implementation

1) **Multi-Source Data Fusion Module**: Configure multi-source access, execute cleaning, normalization and layered fusion, provide feature query APIs and full process logs.
2) **Intelligent Matching Module**: Accept batch orders, invoke improved PPO models to output Pareto optimal matching candidate sets.
3) **Closed-Loop Control Module**: Continuously listen to execution feedback, identify disturbances, trigger auto-rescheduling and record all adjustment logs.
4) **Visual Early Warning Module**: Display regional resource layout, real-time orders and operational indicators with pop-up alerts for overload and performance risks.

7. Comprehensive Experimental Verification and Result Analysis

7.1 Experimental Setup & Metrics

Hardware: 2 cloud servers + 4 edge gateways. Software: OS, databases, middleware and model inference services. A metropolitan logistics dataset is split into 70% training, 15% validation and 15% test subsets. Metrics cover data fusion, resource matching and system operation performance.

7.2 Comparative Experiments

Table 6. compares the proposed system against traditional Platform A under normal, peak and disturbance scenarios

Indicator	Platform A	Proposed System	Optimization
Matching Accuracy	80.14%	91.78%	+11.64%
Resource Idle Rate	17.35%	7.73%	−9.62%
Order Cycle Duration	12.03 h	10.33 h	−14.13%
Disturbance Fulfillment Rate	73.66%	89.84%	+16.18%
Single Batch Inference Latency	426 ms	274 ms	−35.68%

Results prove obvious performance gains in matching precision, resource utilization, delivery cycle, anti-disturbance capacity and inference speed. Data fusion improves input quality; optimized PPO elevates allocation efficiency; closed-loop control greatly strengthens emergency order handling.

7.3 Result Discussion

Massive order surges slightly reduce matching accuracy due to expanded state space. Future work will adopt lightweight models and heuristic pre-filtering to mitigate this issue. Experiments fully validate the integrated engineering scheme of data fusion, intelligent matching and closed-loop control.

8. Conclusions and Future Prospects

8.1 Research Conclusions

Aiming at fragmented logistics data, static matching rules and missing supply chain closed-loop regulation, this paper completes modeling, algorithm optimization, mechanism design and system development with four core outcomes:

1) An entropy weight-attention layered fusion model processes five heterogeneous logistics data types, suppressing noise and missing-value interference and boosting feature integrity.
2) A multi-constraint matching mathematical model and attention-enhanced PPO algorithm with multi-objective reward balance cost, timeliness, utilization and carbon emissions; ablation tests verify its superiority.
3) A full closed-loop control framework "Perception-Matching-Scheduling-Execution-Feedback-Re-Decision" significantly improves fulfillment under vehicle breakdown and other sudden disruptions.
4) A four-layer cloud-edge collaborative intelligent control system is fully developed. Real-data tests show 11.64% higher matching accuracy and 14.13%

shorter order cycles versus traditional platforms, verifying engineering practicability.

8.2 Limitations

The dataset only covers one metropolitan area; cross-provincial generalization needs further validation. Ultra-large order volumes increase inference overhead. The research simplifies multi-stakeholder game relations without detailed interest analysis.

8.3 Future Research Directions

1) Adopt large language models to parse complex business semantics and deduce disturbance logic for robust abnormal scenario decision-making.
2) Integrate digital twin simulation for large-scale logistics scenario deduction.
3) Embed full-link refined carbon footprint calculation into optimization objectives to advance green logistics matching under dual-carbon goals.

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