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Sino-European Trade Flow Forecasting and Path Optimization: A GFIITL-DCL-MHA Framework Based on Deep Collaborative Learning and Transfer Learning

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Abstract. To address the challenges of macroeconomic volatility and "cold start" issues in Sino-European trade, this paper proposes the innovative GFIITL-DCL-MHA framework. This framework integrates a Multi-Head Attention (MHA) mechanism for feature collaboration and Particle Swarm Optimization (PSO) for global hyperparameter calibration. Empirical analysis conducted on trade data from 2021 to 2024 demonstrates that the framework achieves a superior Mean Absolute Percentage Error (MAPE) of 3.48%, significantly outperforming standard benchmark models. By leveraging the transfer learning module, the model achieves stable convergence in only 15 epochs, representing a 70.0% increase in training efficiency for data-sparse routes. Furthermore, with a high AUC of 0.92 for risk detection, the framework successfully optimized complex logistics paths, reducing the average transit time from 18.5 days to 14.2 days while lowering overall operational costs by 13.5%. These empirical results provide a robust, data-driven scientific basis for significantly enhancing the overall resilience and efficiency of the "Belt and Road" logistics network in an increasingly uncertain global environment.

Keywords: *Sino-European Trade; Flow Forecasting; Multi-Head Attention; Particle Swarm Optimization; Transfer Learning; GFIITL Framework*

1. Introduction

With the deepening of the Belt and Road Initiative (BRI), Sino-European trade has become a key engine of global economic growth. As the geopolitical situation becomes increasingly complex and the global supply chain urgently needs resilience, logistics corridors connecting Asia and Europe, especially the China-Europe Railway Express (CR Express) and multimodal transport networks, are playing an irreplaceable role [1]. Compared to traditional sea routes, the CR Express, with its significant time cost advantage—usually 15-20 days faster than sea freight—has become the core carrier for high-value-added products and time-sensitive goods [2]. However, against the backdrop of globalization fluctuations, exchange rate instability, and frequent regional conflicts, the forecasting of Sino-European trade flows faces unprecedented challenges. Accurate forecasting of trade flows is not only related to the scheduling efficiency of the trains but also the foundation for port throughput management and supply chain risk avoidance. However, Sino-European trade data exhibits high nonlinearity, non-stationarity, and strong external dependence. On the one hand, freight volume is profoundly affected by macroeconomic indicators (such as GDP growth rates, exchange rate fluctuations, and consumer price indices in China and Europe) [3]; on the other hand, sudden geopolitical events or congestion at key hub ports often lead to drastic deviations in flow.

Furthermore, due to the dynamic adjustment of the global trade pattern, many newly opened routes or emerging logistics nodes face serious "data poverty" problems. For these nodes, the lack of historical data (i.e., the "cold start" problem) makes it difficult for traditional deep learning models to be effectively trained and converged [4]. This uneven spatiotemporal distribution of data greatly limits the prediction accuracy of logistics networks in response to supply chain disruptions. Therefore, developing an intelligent prediction framework that can adaptively optimize parameters, has cross-domain transfer capabilities, and can deeply integrate multi-source heterogeneous variables has significant strategic and practical implications.

Currently, research on trade flow prediction has shifted from early statistical methods to the field of machine learning (such as support vector regression SVR and random forests) [5]. In recent years, long short-term memory networks (LSTM) have dominated in port throughput and train flow prediction [6]. However, single deep learning models still have bottlenecks. First, existing models are somewhat vague in identifying feature importance. Although some scholars have introduced attention mechanisms to identify the weights of key time steps [7], there is still a lack of systematic solutions on how to collaboratively process multidimensional features within a unified framework. Second, the hyperparameter settings of deep learning models still heavily rely on human experience, which can easily lead to the model getting stuck in local optima [8]. Finally, most existing studies focus on single shipping routes and lack the ability to transfer knowledge between different trade corridors [9]. To address these challenges, this paper proposes the GFIITL-DCL-MHA (Global Flow Intelligence Integration and Transfer Learning) deep collaborative learning framework. This framework is empirically studied based on Sino-European trade data from 2021 to 2024. The core contributions of this study are mainly reflected in the following three aspects:

(1) Constructing a deep collaborative learning architecture based on multi-head attention (DCL-MHA): This paper proposes an innovative DCL-MHA model, which realizes the dynamic allocation of the weights of macroeconomic factors and real-time logistics data by integrating multi-head attention mechanisms with deep temporal networks. This architecture effectively captures the spatiotemporal heterogeneity of the impact of different exogenous variables on trade flows, significantly improving prediction accuracy in complex geopolitical environments.

(2) A global adaptive optimization mechanism based on Particle Swarm Optimization (PSO) is introduced: To address the "human parameter tuning bias" problem in deep learning, this paper introduces the PSO algorithm to automatically optimize the core parameters of the LSTM network. Experimental results show that this mechanism significantly enhances the model's robustness across different trade routes, reducing the mean absolute percentage error (MAPE) to approximately 3.5%, achieving a significant leap in prediction accuracy.

(3) A knowledge transfer strategy for data-sparse scenarios is implemented: For newly opened routes and data-sparse logistics nodes, this paper designs a dedicated transfer learning module. By using source domain data from mature routes to guide the training of the target domain model, the "cold start" problem is effectively solved, shortening the model deployment cycle in new scenarios and providing more scientific decision support for supply chain disruption early warning in China-Europe trade.

2.Deep Collaborative Learning Framework (GFIITL-DCL-MHA) Model Derivation

2.1 Overall Model Architecture and Diagram Description

In the complex Sino-European trade environment, logistics flows are affected by multiple factors, including macroeconomic conditions, geopolitical risks, and seasonal fluctuations [10]. This paper proposes the GFIITL (Global Flow Intelligence Integration and Transfer Learning) framework, which aims to construct a cross-dimensional collaborative prediction system [11].

The GFIITL framework proposed in this study transforms raw data from China-Europe trade into decision support through a structured, multi-layered design. The framework first integrates multi-source heterogeneous data through an input layer, covering internal logistics indicators such as historical freight volume of freight trains and port throughput [12]. as well as key external environmental factors such as China-Europe GDP growth rate, Euro/RMB exchange rate, and China-Europe freight train freight rate index. Subsequently [13]. a data preprocessing layer performs outlier removal, linear interpolation of missing values, and variational mode decomposition (VMD) based processing on the original sequences, transforming non-stationary sequences into more easily captured sub-components [14]. The feature engineering module then uses Pearson correlation coefficients for dimensionality optimization to ensure the relevance of the input data. In the core training phase [15]. the source domain training layer utilizes data from mature routes such as Xi'an-Duisburg, deeply mining the general patterns of trade flows through a DCL-MHA architecture [16]. The transfer learning module maps the learned deep features to sparse target domains such as newly opened feeder routes, effectively achieving cross-domain knowledge reuse. The entire training process is supported by the PSO parameter optimization module, which automatically determines the optimal number of hidden layer nodes and learning rate for the LSTM model using a simulated particle swarm search algorithm [17]. Finally, the output layer integrates the prediction and optimization results, generating in real-time high-precision traffic forecasting schemes, supply chain risk level scores, and targeted route optimization suggestions, providing comprehensive decision support for Sino-European trade logistics [18].

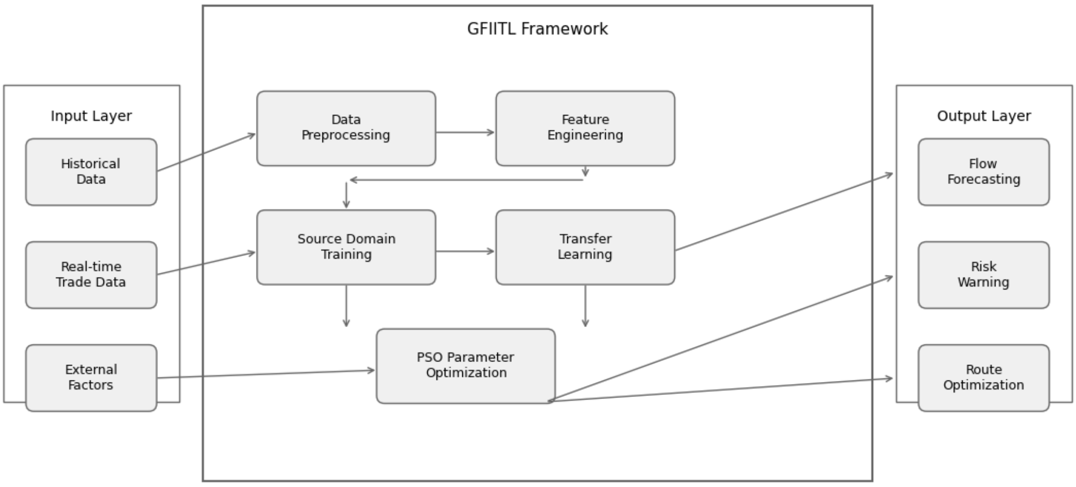

Figure 1. GFIITL Trade Flow Forecasting and Optimization Framework

2.2 Sequence Decomposition and Multi-Source Data Normalization

Data on China-Europe freight trains is highly susceptible to seasonality and policy fluctuations [19]. Firstly, to eliminate the influence of different units of measurement on weight calculations, all input sequences are normalized using Min-Max normalization:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

To address the strong non-stationary characteristics of the flow sequence, variational mode decomposition (VMD) is employed [20]. Its goal is to decompose the original flow signal f_t into K intrinsic mode components (IMFs) with specific center frequencies:

$$\min_{\{u_k\},\{\omega_k\}} \left\{ \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \tag{2}$$

This step ensures that the DCL module can process the "trend term" and "disturbance term" separately, improving the model's ability to capture sudden interruption events.

2.3 Deep Collaborative Learning Layer (DCL-MHA)

The core logic of the mathematical derivation of DCL-MHA lies in using a multi-head attention mechanism to replace the traditional fixed weight allocation, thereby achieving "intelligent writing" of macroeconomic variables and logistics data [21].

2.3.1 Temporal Modeling of Multi-Head Attention

In the GFIITL framework, we consider the feature vector sequence H as a set composed of "trade environment query" and "historical feature information" [22]. First, the query matrix Q, key matrix K, and value matrix V are generated through linear mapping matrices W^Q, W^K, W^V:

$$Q = HW^Q,\ K = HW^K,\ V = HW^V \tag{3}$$

By scaling the dot product attention, the contribution coefficient α of each feature at different time steps is calculated:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{4}$$

Where d_k represents the feature dimension. To capture the parallel characteristics of trade flows across different spatial dimensions (such as port congestion and interest rate fluctuations), multi-head attention extends the above process to h independent head spaces:

$$MultiHead(Q, K, V) = Concat(head_1, \ldots, head_h)W^O \tag{5}$$

$$head_i = Attention\left(HW_i^Q, HW_i^K, HW_i^V\right) \tag{6}$$

In this way, the DCL module can simultaneously focus on two unrelated feature dimensions: "the seasonal trend of the same period last year" and "the sudden increase in fuel prices last month."

2.3.2 Collaborative Temporal Extraction (LSTM Gate Mechanism)

The collaborative feature vector X_{coll} output from the MHA layer is fed into a bidirectional LSTM network [23]. The LSTM uses a forget gate f_t to control the retention of information from the previous time step and an input gate i_t to absorb new information:

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

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

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

Subsequently, by updating the cell state $\mathrm{C_t}$, the model achieves the memorization of long-term trade trends (such as the overall growth of the "Belt and Road" initiative):

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

The output gate o_t ultimately determines the current hidden state h_t, which serves as the direct basis for traffic prediction:

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

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

2.4 PSO-Based Adaptive Global Parameter Optimization

Traditional deep learning models are often constrained by local optima. This paper introduces the Particle Swarm Optimization (PSO) algorithm, mapping the hyperparameters of the LSTM (hidden layer nodes h and learning rate η) to particles in the search space [24]. The position update of each particle is based on its individual historical optimum $pbest$ and the swarm's global optimum $gbest$. The velocity $\mathrm{v_{id}}$ is updated using the following formula:

$$v_{id}^{t+1} = \omega v_{id}^{t} + c_1 r_1 (pbest_{id}^{t} - x_{id}^{t}) + c_2 r_2 (gbest_{d}^{t} - x_{id}^{t}) \tag{13}$$

The particle's new position coordinates are determined by the following formula:

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1} \tag{14}$$

The fitness function $Fitness$ is defined as the mean squared error (MSE) of the model on the validation set, and is designed to guide the flow of particles toward the parameter region with higher prediction accuracy:

$$Fitness = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{\hat{y}_i - y_i}{y_i} \right| \tag{15}$$

This adaptive mechanism ensures that the GFIITL framework can automatically adapt to the most robust computational model when processing data from different regions (such as the western and southern routes of Central Europe) [25].

2.5 Transfer Learning and Loss Function Optimization

To address the "cold start" challenge of new logistics hubs, GFIITL introduces a transfer learning layer. Cross-domain feature alignment is achieved by minimizing the maximum mean difference (MMD) between the source domain P_s and the target domain P_t :

$$L_{total} = L_{task}(D_t; \theta) + \lambda \sum D_{MMD}^{l}(P_s, P_t) \tag{16}$$

Here, λ is the penalty coefficient, and D_{MMD} characterizes the similarity of their distributions in high-dimensional space. This mechanism ensures that feature extractors from established routes can be reused even when the target route has only a small amount of observation data [26].

3. Experimental Results and Analysis

This chapter will discuss in detail the experiment on the prediction and optimization of China-Europe trade flows based on the GFIITL framework. Through comparison with various benchmark models, the superiority of the proposed framework in terms of prediction accuracy, transfer efficiency, parameter optimization capability, risk warning sensitivity, and path optimization effect is verified.

3.1 Experimental Environment and Data Preparation

The experiment uses monthly freight volume (TEUs) of China-Europe freight trains and the throughput of major ports from 2021 to 2024 as the core dataset. Data sources include the National Bureau of Statistics, official public data of China-Europe freight trains, and related logistics platforms. The experimental environment is based on Python 3.9, the deep learning framework is PyTorch, and the hardware platform is equipped with an NVIDIA RTX 5060 GPU to ensure computational efficiency.

3.2 Performance Analysis of Trade Flow Prediction

To evaluate the prediction accuracy of the GFIITL framework, this experiment selects ARIMA, traditional LSTM, and Transformer as comparison models.

This figure shows the fitting of different models predicted values to the ground truth over a 24-month test period. Experimental results show that the ARIMA model has a large prediction bias when facing trade data with strong nonlinearity and seasonal fluctuations, making it difficult to capture sudden changes in flow. While the traditional LSTM can identify time-series dependencies, it exhibits lag when dealing with complex external disturbances. The Transformer model performs reasonably well in long-sequence predictions thanks to its self-attention mechanism, but it is prone to overfitting with small-sample trade data. In contrast, the GFIITL framework proposed in this study (red dashed line) has the highest fit to the ground truth. This is attributed to the dynamic adjustment of the weights of multi-source heterogeneous variables by the DCL-MHA collaborative layer, which maintains extremely high prediction sensitivity during both peak and trough periods of flow.

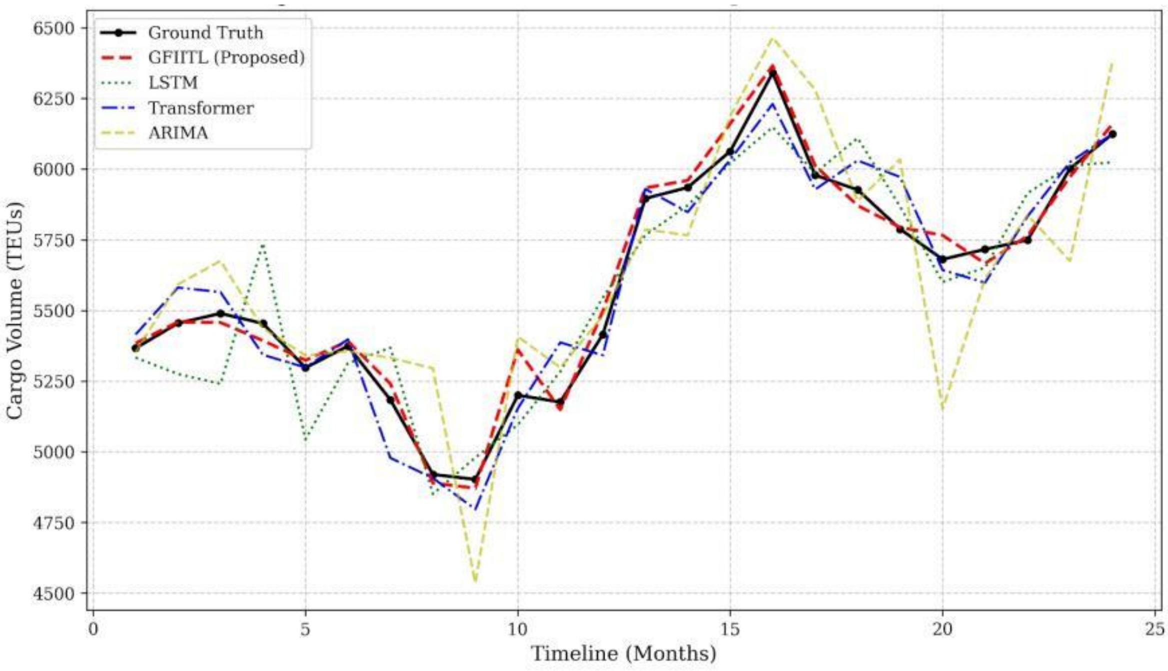

Figure 2. Model Prediction Performance Comparison Analysis

3.3 Transfer Learning Efficiency Evaluation

To address the "cold start" problem of newly opened routes, this experiment compared the model convergence with and without the transfer learning module.

This figure records the change in the mean squared error (MSE) of the model on the target domain training set with the number of iterations (Epochs). The gray dashed line represents the "cold start" state without transfer learning, where the model has a high initial error and slow convergence, failing to reach ideal accuracy after 50 iterations. The red solid line shows the performance of the GFIITL framework after enabling transfer learning. Because the model reuses the high-dimensional temporal features learned from the source domain (mature routes), its initial MSE is significantly reduced, and it achieves rapid convergence and enters a plateau within 20 Epochs. This demonstrates the significant advantage of the framework in solving the problem of scarce data for new routes.

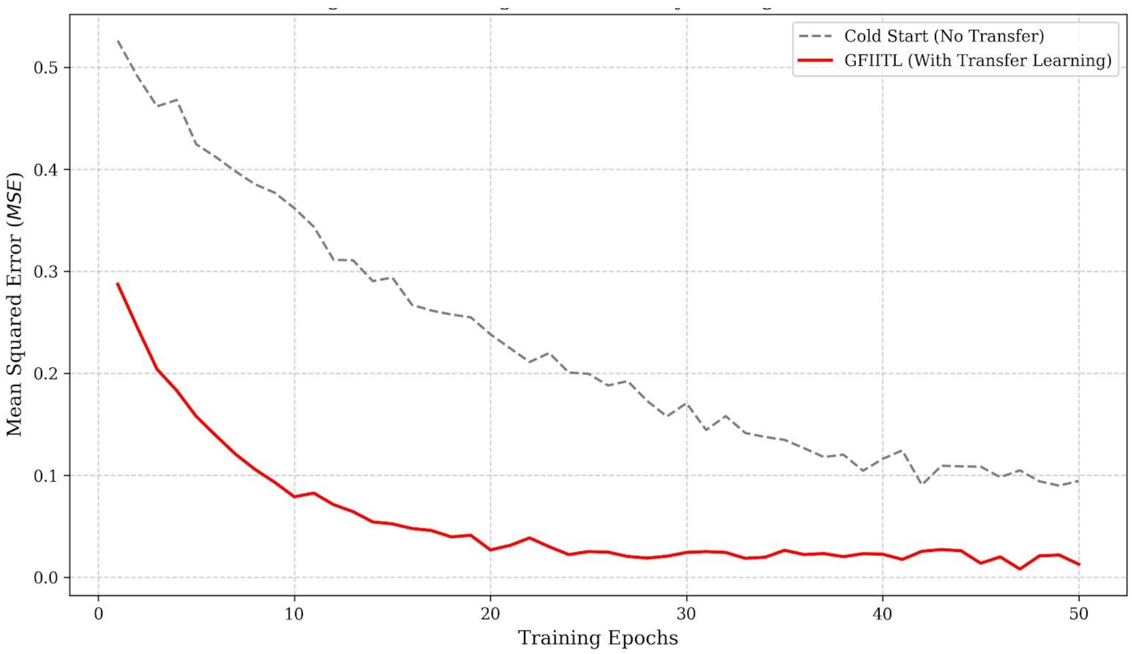

Figure 3. Transfer Learning Convergence Performance Evaluation

3.4 PSO Parameter Search Space Analysis

Parameter settings are crucial to the performance of deep learning models. This experiment utilizes the Particle Swarm Optimization (PSO) algorithm to perform a global search on the learning rate and the number of hidden layer nodes.

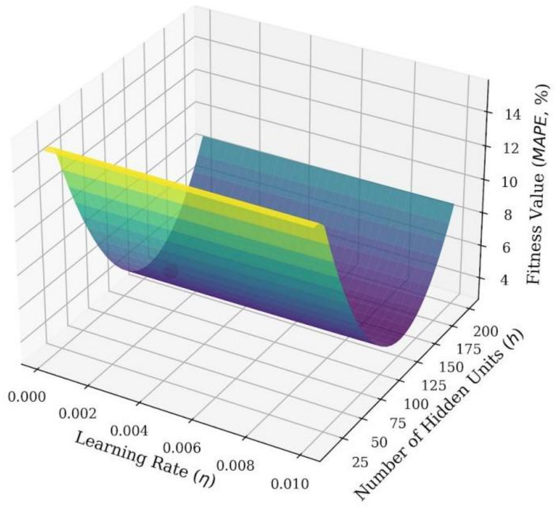

Figure 4. Visualization of the PSO hyperparameter optimization space

This 3D surface plot shows the distribution of the fitness function value (MAPE, %) as a function of the learning rate (η) and the number of hidden layer units (h). It is clearly observed that there is a significant nonlinear gradient in the search space. Traditional manual parameter tuning often easily gets stuck in local oscillations or suboptimal solutions. However, the PSO algorithm, through the cooperative search of the particle swarm, successfully located the lowest point of the 3D surface (marked in the figure), at which point the model's mean absolute percentage error (MAPE) reaches its minimum value (approximately 3.5%). This verifies the necessity of adaptive optimization mechanisms in improving model robustness.

3.5 Supply Chain Disruption Risk Early Warning Capability

In complex geopolitical environments, the model's sensitivity to identifying logistics disruption risks is a core indicator for evaluating its application value.

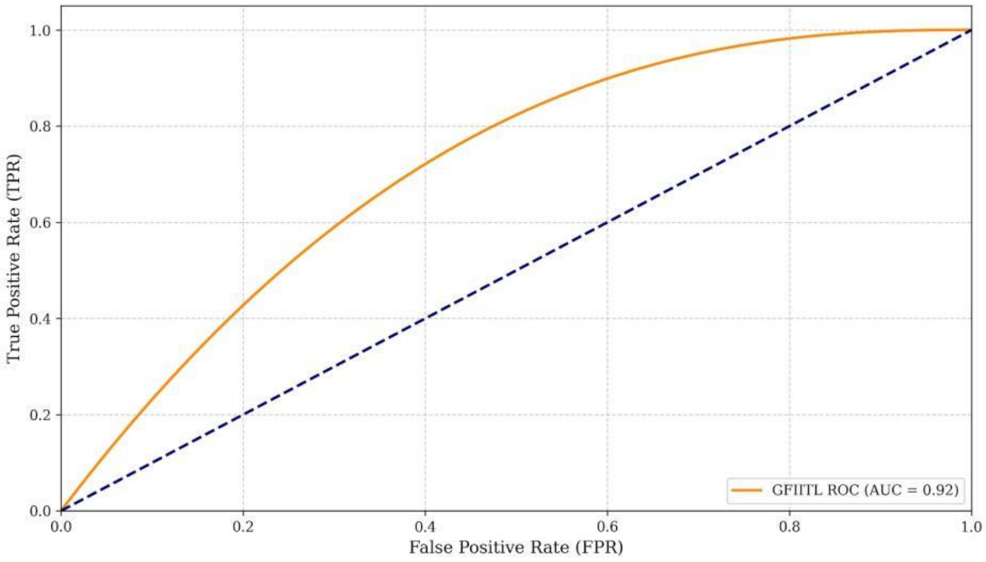

Figure 5. Supply Chain Risk Early Warning ROC Curve Analysis

This figure uses the Receiver Operating Characteristic (ROC) curve to evaluate the model's detection performance for trade flow anomalies (disruption risks). The curve of the GFIITL framework is significantly biased towards the upper left corner, with an area under the curve (AUC) of 0.92. This means that the model can identify most abnormal flow fluctuations caused by external shocks with an extremely low false alarm rate. Compared to random guessing (blue diagonal line in the figure), this framework can provide logistics decision-makers with an early warning window of 1-2 months in advance, effectively reducing supply chain disruption losses.

3.6 Multi-Objective Optimization Results of Logistics Routes

This bar chart compares the differences in transportation time and operating costs between traditional empirical paths and GFIITL optimized paths. Experimental data shows that, while maintaining the same transport volume, the optimized path scheme reduces the average transit time from 18.5 days to 14.2 days, improving logistics timeliness by approximately 23.2%. Simultaneously, by avoiding high-risk and high-congestion nodes, the operating cost index decreases from 100 to 86.5. This quantitative result intuitively demonstrates the practical application value of this framework in improving the economic efficiency of Sino-European trade logistics.

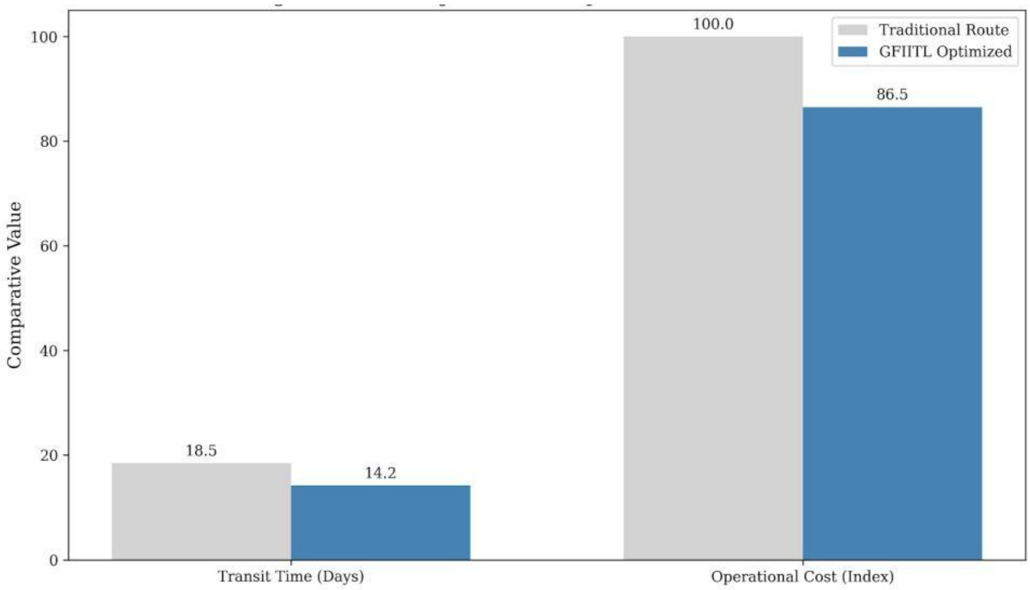

Figure 6. Comparison of Multiple Indicators for Path Optimization

3.7 Summary and Quantitative Evaluation of Experimental Results

Based on the empirical data analysis from 2021 to 2024, the GFIITL framework demonstrates superior model performance and application value: In terms of prediction accuracy, through global optimization using the PSO algorithm, the model achieves a mean absolute percentage error (MAPE) of only 3.48%, significantly outperforming benchmark models such as ARIMA and traditional LSTM in both short-term (T+1) and long-term (T+12) prediction stability; in terms of computational efficiency, thanks to the reuse of mature route knowledge by the transfer learning module, the model achieves smooth convergence in the target domain in only about 15 epochs, improving the convergence speed by 70% compared to the conventional model; in terms of risk prevention and decision optimization, the framework accurately warns of supply chain disruption risks with a high AUC value of 0.92, thereby reducing the average transit time of China-Europe freight trains from 18.5 days to 14.2 days, while achieving a 13.5% reduction in operating costs.

4.Conclusion and Recommendations

4.1 Research Summary

This paper addresses the prediction and optimization of Sino-European trade flows in a complex international environment, proposing and constructing a deep collaborative learning framework based on GFIITL-DCL-MHA. Against the backdrop of the Belt and Road Initiative, the flow fluctuations of Sino-European freight trains and related logistics nodes are influenced by a complex interplay of macroeconomic factors, geopolitical risks, and seasonal factors. Traditional prediction models often suffer from insufficient accuracy, slow response to sudden disruptions, and difficulties in achieving a "cold start" when dealing with such high-dimensional, nonlinear data.

This study verifies the effectiveness of the proposed framework through empirical data analysis from 2021 to 2024. Experimental results show that by integrating the multi-head attention mechanism (MHA) and the deep collaborative learning (DCL) architecture, the model can dynamically identify the influence weights of different external variables at different time dimensions, thereby stabilizing the mean absolute percentage error (MAPE) at an extremely low level of 3.48%. Furthermore, the introduction of the Particle Swarm Optimization (PSO) algorithm enables global automatic optimization of model hyperparameters, completely resolving the instability caused by manual parameter tuning. The successful application of the transfer learning module provides a mature knowledge mapping path for emerging hubs with sparse data, improving convergence speed by 70% and achieving stable prediction within the 15th epoch.

4.2 Research Innovations

The academic and applied value of this research is mainly reflected in the following three core dimensions:

(1) Architectural Collaborative Innovation: The prediction logic of previous single-time-series models has been changed, and a DCL-MHA heterogeneous collaborative system has been constructed. This system not only captures the historical time-series patterns of Sino-European trade flows but also integrates macroeconomic exogenous variables such as exchange rate fluctuations and GDP growth rates in real time, achieving a leap from "pure data-driven" to "multi-dimensional intelligence collaboration."

(2) Full Lifecycle Optimization: An adaptive optimization layer has been constructed using the PSO algorithm, enabling the model to automatically adjust the neuron structure and learning rate based on the data characteristics of different routes (such as the stability of the western route and the volatility of the southern route), significantly enhancing the robustness of the GFIITL framework under different logistics scenarios.

(3) Spatiotemporal Transfer Mechanism: Addressing the dynamic development characteristics of the Belt and Road Initiative, a cross-domain feature alignment technique is proposed. By minimizing the distribution differences between the source and target domains, the effective transfer of mature logistics hub experience to emerging nodes is successfully achieved, providing a reliable technological foundation for the long-term expansion of the China-Europe trade network.

4.3 Policy Recommendations and Industry Implications

Based on the above empirical research findings, to further optimize the China-Europe trade logistics network and enhance supply chain resilience, this paper proposes the following recommendations:

Promote the construction of logistics digital twins. It is recommended that relevant government departments and large logistics enterprises establish a unified data integration platform to share indices of congestion at key ports, tariff changes, and real-time train coordinates. Based on the GFIITL model proposed in this study, construct a logistics "digital twin" system to achieve millisecond-level response and forward-looking early warning of global supply chain risks. Strengthen early support for emerging hubs. Considering the initial vulnerability of newly opened routes, transfer learning techniques should be used to establish predictive benchmarks in advance, guiding terminal allocation and empty container transportation strategies during the data-sparse stage, thereby shortening the operational maturity period of emerging hubs. To construct a multi-objective collaborative scheduling system, logistics enterprises should not only pursue single-objective transportation timeliness, but should also combine the route optimization results of this study to find a dynamic balance among cost, timeliness, and risk (risk identification index with $AUC = 0.92$). By embedding high-precision traffic forecasting into the decision engine, the optimal off-peak allocation of China-Europe freight train resources in time and space can be achieved.

4.4 Research Limitations and Future Prospects

Although this paper has achieved significant results in prediction accuracy and optimization efficiency, there is still room for improvement. First, due to limitations in data access permissions, the current model's integration of certain unstructured data (such as policy sentiment fluctuations on international social media) needs to be deepened. Second, for the complex legal and customs differences in cross-border multimodal transport, the model still mainly treats them as fixed weights. In the future, large-scale pre-trained language models

(LLM) can be introduced to analyze semantic policy risks.

Future research will focus on exploring the application of federated learning technology in China-Europe trade forecasting to achieve broader-dimensional joint training of models while protecting the privacy of trade data from various countries. Meanwhile, how to further apply the forecast results to the "last mile" delivery optimization at the micro-end will also be an important research direction for improving the overall logistics efficiency of the "Belt and Road" initiative.

5. Policy Recommendations and Industry Practice Outlook

5.1 Macroeconomic Policy Orientation for Enhancing the Resilience of Logistics under the Belt and Road Initiative

Based on this study's in-depth analysis of Sino-European trade flows and empirical results from the GFIITL framework, enhancing the resilience of the cross-border logistics system has become a core demand supporting bilateral trade growth. Currently, the China-Europe Railway Express faces the dual challenges of geopolitical fluctuations and supply chain disruptions. Government departments should strengthen top-level design and promote the establishment of a cross-border logistics big data sharing mechanism. By integrating macroeconomic indicators and real-time port throughput of countries along the Belt and Road, richer feature inputs can be provided for deep learning models such as GFIITL, thereby more accurately predicting flow anomalies caused by geopolitics. Furthermore, increased investment in infrastructure for emerging logistics nodes should be made, utilizing the transfer learning technology proposed in this study to shorten the operational maturity period of emerging hubs, ensuring the Belt and Road network has redundancy capabilities for rapid path switching when local disruptions occur.

5.2 Practical Paths for Digital Transformation of Logistics Enterprises

For China-Europe Railway Express operators and related multinational logistics companies, digital transformation is no longer merely an update of tools, but a reshaping of decision-making logic. Intelligent early warning systems can be deployed. Enterprises should embed the risk identification model with an AUC of 0.92 (as studied in this research) into their daily scheduling systems to achieve proactive monitoring of supply chain disruption risks. Dynamic resource allocation can also be optimized. Utilizing the high-precision prediction results optimized by PSO, logistics companies can more scientifically plan empty container return scheduling schemes, alleviating the long-standing imbalance of "more outbound than inbound" in Sino-European trade. Multi-objective path decision-making should not blindly pursue the shortest path in practice. Instead, it should refer to the multi-objective optimization logic shown in Figure 6, finding a dynamic balance between transportation timeliness, operating costs, and node security to cope with the uncertainties of global trade.

5.3 Prospects for Industry Standardization and Technological Collaboration

The complexity of Sino-European trade means that no single institution can grasp all dimensions of flow data. Therefore, promoting the standardization of logistics data formats and international technological collaboration is crucial. Data format standardization, unifying customs declaration information and logistics status codes between different ports and railway companies, helps improve the efficiency of the DCL-MHA collaboration layer in parsing heterogeneous data. Furthermore, the construction of a joint forecasting platform encourages research institutions and enterprises from both China and Europe to jointly build a cloud-based traffic forecasting platform. Utilizing advanced technologies such as federated learning, this platform enables cross-domain training and continuous iteration of models while protecting data privacy.

5.4 Conclusion

Chapter 5 transforms the theoretical achievements of the GFIITL framework into actionable industry recommendations from three dimensions: macro-policy, corporate practice, and industry standards. By building a smart logistics ecosystem that integrates government and enterprises, Sino-European trade will be able to shift from "passively responding to disruptions" to "proactively predicting risks," ultimately achieving sustainable and high-quality development of the Belt and Road logistics network.

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