Multi-Task Learning-Based Optimization for Cross-Regional Logistics Scheduling and Transportation Efficiency

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Keywords: multi-task learning, cross-regional logistics scheduling, task allocation, path planning, transportation time prediction, optimization algorithm

Received: March 27, 2025

With the development of globalization and digitalization, improving the efficiency of cross-regional logistics scheduling has become a key issue. Traditional logistics optimization algorithms have limitations in complex multi-task scenarios. Multi-task learning, as a branch of deep learning, provides a new idea for solving this problem. This paper proposes a logistics scheduling optimization strategy and model based on multi-task learning. This study is evaluated based on a real data set containing 5,000 cross-regional logistics order records and a simulated data set covering 300 different transportation scenarios. The real data set comes from the logistics business of 5 major logistics hub cities in China and their radiating areas within half a year, and the simulated data set is constructed by comprehensively considering factors such as terrain, traffic conditions, and order density in different regions. The model has achieved an order allocation accuracy of 92%, the path planning cost is reduced by 25% compared with the traditional method, and the transportation time prediction error is controlled within ±3 hours. Among them, the order allocation accuracy is calculated as the proportion of the number of correctly allocated orders to the total number of orders, the path planning cost is obtained by combining the actual transportation mileage with the unit mileage cost, and the transportation time prediction error is the average of the absolute value of the difference between the predicted time and the actual transportation time. The model has achieved an order allocation accuracy of 92%, the path planning cost is reduced by 25% compared with the traditional method, and the transportation time prediction error is controlled within ±3 hours. Among them, the order allocation accuracy is calculated as the ratio of the number of correctly allocated orders to the total number of orders. The path planning cost is obtained by combining the actual transportation mileage with the unit mileage cost. The transportation time prediction error is the average of the absolute value of the difference between the predicted time and the actual transportation time.

Povzetek: Članek uvaja večopravilno učenje za čezregionalno logistiko, združuje dodeljevanje naročil, načrtovanje poti in napovedovanje časov prevoza.

1 Introduction

With the deepening of globalization and digitalization, logistics, as an important structure connecting transportation, trade and consumption, has become an indispensable technology and service field for economic development. Especially in cross-regional logistics scheduling, due to the differences in regional demand, uneven distribution of resources and the complexity of transportation methods [1], the scheduling process faces a wealth of practical problems that cannot be solved by traditional optimal decision-making methods. How to maximize the system transportation efficiency while ensuring the logistics response speed and cost control has become a common concern of academia and industry [2].

Traditional logistics optimization algorithms, such as natural number series algorithms and genetic algorithms, although somewhat effective in solving single tasks, have become ineffective for multiple tasks that are interrelated in complex scenarios, especially cross-regional logistics that require integrated transportation planning, transshipment allocation, and time control. The long solution time and distortions in the actual operation process caused by these algorithms make it difficult for them to complete tasks in modern logistics scenarios [3]. Multi-task learning (MTL), as an important branch of deep learning, is particularly suitable for scenarios that require tail-to-tail association and information sharing. MTL can significantly improve learning efficiency and the overall performance of the model by learning multiple related tasks simultaneously in the same model. Although there is far from sufficient research to apply this method to cross-regional logistics scheduling, the efficiency improvement brought by the realization of solutions in this field is obvious [4,5].

In cross-regional logistics scheduling scenarios, most traditional solutions focus on optimizing a single task, such as solving the shortest distance transportation and the best transshipment pattern plan. However, when the region is large, such solutions are small-scale. Especially in cross-regional scenarios with high bandwidth and capacity, due to information insignificance and single-point optimization, the regional bandwidth is too low, coupled with communication association and resource allocation problems. MTL can meet the actual cross-regional scheduling needs and maximize the scale of the scenario through tail-to-tail resource sharing and better scenario solutions [6].

In the modern economic system, improving scheduling efficiency and decision-making planning is the key to achieving cross-scenario automation and process optimization. With the deepening of internal and external connections among industries, logistics and transportation management are facing unprecedented challenges. To meet these challenges, this paper proposes a logistics scheduling optimization strategy based on a multi-task learning model. The strategy aims to significantly improve the efficiency of dispatch date scheduling in actual operations by optimizing transportation scheduling, while addressing the complexity and trade-off properties of large-scale scheduling. We simulate the best hybrid solution to adapt to challenges of different scales and ensure that the optimal solution can be found in various situations. This multi-task learning model can effectively integrate the learning process of multiple related tasks, thereby improving the overall scheduling efficiency [7].

The focus of this paper is to develop an efficient scheduling method that can expand regional coverage at the planning level. We implement a hybrid combination of data, bring this data into the planning process, and design a shared loading structure to enhance the actual efficiency of field operations. By optimizing multiple tasks (such as subtask allocation, tax management, and maintenance loading), our model not only solves the problem of cross-regional mobilization, but also promotes the comprehensive allocation and utilization of resources [8]. In addition, our strategy also includes cultivating and developing intelligent scheduling systems that can continuously learn and adapt to changes in a dynamic environment. This helps to promote the intelligent development of the logistics industry, promote the effective allocation of resources, and thus improve the operational efficiency of the entire supply chain. Ultimately, this approach provides a more flexible and efficient solution for logistics scheduling, supporting enterprises to achieve higher economic benefits and service quality [9].

2. Related work

2.1 Logistics scheduling optimization method

Logistics scheduling optimization plays a vital role in improving distribution efficiency and reducing operating costs. Traditional optimization methods, such as linear programming (LP) and genetic algorithms (GA), are widely used to solve key problems in logistics scheduling. Linear programming methods are widely used to solve vehicle routing problems (VRPs) to improve transportation efficiency by optimizing path selection and distribution task scheduling. However, as the scale and complexity of the problem increase, the computational efficiency and solution accuracy of linear programming in dealing with large-scale problems are subject to certain limitations. Therefore, more innovative methods are needed in real applications to cope with complex scheduling requirements [10,11].

As a heuristic search method, genetic algorithms rely on the evolution mechanism of populations and achieve a balance between global search and local search by introducing operations such as mutation and crossover. Genetic algorithms can effectively deal with complex logistics scheduling problems with multiple decision variables and constraints, but they are prone to fall into local optimal solutions, affecting the efficiency and stability of the solution [12]. To solve this problem, some studies have proposed improved genetic algorithms, such as combining multiple population strategies or dynamically adjusting genetic operation parameters to reduce the risk of the algorithm falling into local optimal solutions, while improving the global search capability and enhancing the stability and solution efficiency of the algorithm [13].

In recent years, deep learning technology has been widely used in logistics scheduling optimization and has shown great potential. The deep reinforcement learning method, which realizes strategy optimization through interaction with the environment, has achieved remarkable results in multi-freight scheduling problems [14]. Deep reinforcement learning can optimize important indicators such as delivery time, fuel consumption, and vehicle utilization through repeated trials and simulations. In particular, in drone delivery, reinforcement learning is applied to path planning. Combined with the attention mechanism and policy gradient optimization, it can dynamically adjust the path according to real-time environmental data, greatly improving the response speed and flexibility of the logistics system and significantly enhancing the system's ability to adapt to changing environments [15].

2.2 Multi-task learning technology

Multi-task learning (MTL) is a technique that optimizes multiple related tasks simultaneously by sharing representations. It has unique advantages in improving the generalization performance of the model and handling the correlation between complex tasks. In recent years, the application of MTL technology in logistics and transportation optimization has gradually become a research hotspot [16]. Specifically, many studies have adopted the MTL method to solve cross-regional logistics scheduling problems. By sharing feature representations between tasks, significant performance improvements have been achieved in multi-dimensional optimization tasks.

For example, rail transit passenger flow prediction models based on multi-task learning have made breakthrough progress. These models introduce residual convolutional networks and nested long short-term memory networks, which can mine deep temporal and spatial features when processing time series data, thereby effectively enhancing the ability to jointly model the passenger flow in and out of stations. This method shares knowledge between multiple tasks, which not only significantly improves the prediction accuracy, but also enhances the robustness of the model and its adaptability to changing environments [17,18].

In the field of logistics, MTL technology has also been widely used in multi-task optimization of vehicle routing problems. In response to the heterogeneous requirements of different tasks for attributes, MTL greatly improves the synergy between tasks by sharing representations between tasks, especially when solving VRP problems with different attributes, it has shown excellent performance. Furthermore, some studies have combined inter-task weight sharing with task-specific layers, which not only improves the zero-shot generalization ability, but also achieves superior performance on multiple data sets, demonstrating the strong potential of MTL in cross-task optimization [19].

2.3 Deficiencies of current research

Although existing research has achieved certain results in the design and algorithm development of logistics scheduling optimization models, it still faces several key challenges. Traditional single-task models are often unable to effectively utilize the correlation between different tasks when facing multi-dimensional logistics demands, which limits their overall optimization effect in practical applications. Although multi-task learning has alleviated this problem to a certain extent, how to scientifically select tasks and reasonably allocate task weights is still an important problem in current multi-task learning methods [20,21]. In addition, the complexity of cross-regional logistics scenarios significantly increases the difficulty of scheduling optimization. There are large differences in logistics demand, traffic conditions, and resource distribution between different regions, which makes the existing models generally lack generalization and adaptability when solving cross-regional scheduling problems. Traditional optimization methods and existing deep learning models still seem to be somewhat powerless when dealing with cross-regional dynamic factors, especially in terms of resource scheduling and transportation efficiency improvement, lacking effective comprehensive consideration and dynamic adjustment mechanisms [22].

As the scale of logistics distribution networks continues to expand and the complexity of the system increases, how to efficiently process large-scale high-dimensional data and achieve real-time response has become a core issue that needs to be solved. Most existing research focuses on the performance of optimization models and algorithms, but rarely involves comprehensive considerations of data quality, system deployment, and practical applications. Future research should pay more attention to how to integrate data from different sources, build more efficient and robust optimization models, and ensure that these models can be seamlessly connected with actual logistics scenarios. This will be a key direction for the development of intelligent logistics scheduling optimization in the future.

Table1: Comparison of logistics scheduling methods

Method	Scheduling Efficiency	Order Allocation Accuracy	Computational Cost	Key Limitations	Solution in This Paper's Model
Linear Programming (LP)	Fast for small-scale, slow for large-scale	High for small-scale, low for large-scale	Low for small-scale, high for large-scale	Complex computation for large-scale	Parallel processing of multiple tasks, coordination between shared layers and task-specific layers to increase speed and reduce costs
Genetic Algorithm (GA)	Average of 4 hours, prone to fluctuations	Approximately 75%, decreases in complex situations	Approximately 300 cost units	Prone to getting trapped in local optimum	Dynamically adjust weights to enhance global search ability
Deep Reinforcement Learning (RL)	Excellent in dynamic environment, long training time	80%	Approximately 400 cost units	Long training time, difficult to model the environment	Share features among multiple tasks to reduce training time

As shown in Table 1, Linear programming is efficient for small-scale logistics scheduling, but for large-scale scenarios, complex computations lead to deteriorated efficiency and increased costs. The model in this paper improves the situation by using a multi-task framework. The genetic algorithm has an average scheduling time of 4 hours, but it is prone to getting trapped in local optimum, affecting the accuracy. In this paper, the problem is solved by dynamically adjusting the weights. Deep reinforcement learning performs well in a dynamic environment, but it has a long training time and high computational cost. This paper utilizes the sharing of features among multiple tasks to reduce the training duration and enhance the adaptability to complex environments.

3 Methodology

This chapter focuses on the problem of cross-regional logistics scheduling. From mathematical modeling, multi-task learning framework design to data processing, the research method and its theoretical basis are elaborated in detail. In order to comprehensively optimize the efficiency of logistics scheduling, this paper adopts the multi-task learning (MTL) method to integrate order allocation, path planning and transportation time prediction into a unified framework. By designing a scientific loss function and optimization strategy, this method can achieve collaborative optimization among multiple tasks and improve the overall system performance.

3.1 Problem modeling

The cross-regional logistics scheduling problem is an important part of the modern logistics system. Its goal is to complete the transportation of all orders at the lowest cost while meeting time and capacity constraints. This problem is essentially a multi-objective optimization problem, covering three core tasks: order allocation, path planning, and transportation time prediction. Traditional methods usually handle these tasks separately, but this single-task optimization method is difficult to fully utilize the correlation between tasks. Therefore, this paper integrates the three tasks into a unified mathematical model through a multi-task learning framework.

Assume that n Orders $\mathrm{O}=\{o_1,o_2,\ldots,o_n\}$ and m Logistics vehicles $\mathrm{V}=\{v_1,v_2,\ldots,v_m\}$. Each order o_i Contains attributes such as weight, origin and destination. Each vehicle v_j With capacity limit capacity_j The goal of the logistics system is to assign all orders to appropriate vehicles and plan reasonable routes, while ensuring that the transportation time meets customer needs and the total transportation cost is minimized. To this end, we define the following variables to x_{ij} represent order o_i. Is it assigned to a vehicle? v_j, which is defined as Formula 1.

$$x_{ij}=\begin{cases}1, & \text{If the Order} o_i \text{ Assigned to A Vehicle } v_j, \\ 0, & \text{If Not}\end{cases} \tag{1}$$

y_{ij} indicates order o_i Along the path $i \to j$ transport, which is defined as Formula 2.

$$y_{ij}=\begin{cases}1, & \text{If the Order} o_i \text{ Via Path } i \to j, \\ 0, & \text{If Not}\end{cases} \tag{2}$$

Based on the above variables, the objective function of the cross-regional logistics scheduling problem can be defined as Formula 3.

$$\min \mathrm{L}=\sum_{i=1}^{n}\sum_{j=1}^{m}c_{ij}x_{ij}+\lambda\sum_{i=1}^{n}\sum_{j=1}^{m}d_{ij}y_{ij} \tag{3}$$

In Formula 3, c_{ij} Indicates order o_i Assigned to vehicle v_j Shipping costs, d_{ij} Indicates order o_i Along the path $i \to j$ The transportation time, λ is the importance weight used to balance transportation cost and time.

To ensure the feasibility of the model, the following constraints need to be met:

Each order must satisfy Formula 4, that is, it is assigned to and only assigned to one vehicle.

$$\sum_{j=1}^{m}x_{ij}=1, \quad \forall i \in \mathrm{O} \tag{4}$$

The total load of each vehicle must not exceed the capacity limit in Formula 5.

$$\sum_{i=1}^{n}x_{ij}\cdot \text{load}_i \le \text{capacity}_j, \quad \forall j \in \mathrm{V} \tag{5}$$

The path planning needs to meet the predetermined time limit in formula 6 .

$$\sum_{i=1}^{n}\sum_{j=1}^{m}d_{ij}y_{ij} \le T, \quad \forall j \in \mathrm{V} \tag{6}$$

In this picture, we see a mathematical model of a logistics scheduling problem. The parameter variables are explained as follows.

x: This is a binary variable that indicates whether the order o_i is assigned to the vehicle v_j. If the order o_i is assigned to the vehicle v_j, then $x_{ij}=1$, otherwise $x_{ij}=0$. y_{ij}: This is also a binary variable that indicates whether the order o_i is transported via the path $i \to j$. If the order o_i is transported via the path $i \to j$, then $y_{ij}=1$, otherwise $y_{ij}=0$.

The objective function (Formula 3) aims to minimize the total transportation cost and time. Where c_{ij} represents the transportation cost of order o_i assigned to vehicle v_j. d_{ij} represents the time it takes for order o_i to be transported via path $i \to j$. λ is an important weight used to balance transportation cost and time. The constraints ensure that each order is assigned to only one vehicle (Equation 4), the total load of each vehicle does not exceed its capacity limit (Equation 5), and the path planning needs to meet the predetermined time limit (Equation 6).

3.2 Optimization algorithm design

To solve the problem of cross-regional logistics scheduling, this paper proposes an optimization algorithm based on multi-task learning (MTL). The model consists of two parts: a shared network layer and a task-specific network layer. The purpose of the shared network layer is to extract the global features of the input data so that each task can share this information, while the task-specific network layer specifically designs an independent structure for each subtask in order to optimize the specific requirements between tasks.

3.2.1 Model Architecture

Assume that the input features are $\mathbf{x}$, which contains logistics information from multiple regions (such as order data, traffic conditions, resource distribution, etc.). The role of the shared network layer is to extract common global information from the input features and output the feature representation $\mathbf{z}$, and its calculation formula is Formula 7.

$$\mathbf{z}=f_{\text{shared}}(\mathbf{x};\theta_{\text{shared}}) \tag{7}$$

In Formula 7, θ_{shared} is the parameter of the shared network layer. Next, the task-specific network layer is represented according to the shared feature $\mathbf{z}$ Design independent structures for each subtask, including: order allocation ($L_{\text{allocation}}$) , Path Planning (L_{path}) and transportation time prediction (L_{time}). The prediction results of each subtask $\mathbf{y}_{\text{task}}$ Given by formula 8.

$$\mathbf{y}_{\text{task}} = f_{\text{task}}(\mathbf{z}; \theta_{\text{task}}) \quad (8)$$

In Formula 8, θ_{task} are the parameters of the task-specific network.

The input data of the shared network layer contains information closely related to order allocation and path planning, which involves the content represented by variables x_{ij} and y_{ij}. When extracting features from the input data, the discrete x_{ij} and y_{ij} information is converted into continuous feature vectors through encoding for processing by the neural network. For example, for x_{ij}, if the order o_i is assigned to the vehicle v_j (i.e., $x_{ij} = 1$), the corresponding position in the input feature vector is set to a specific value (such as 1), and if it is not assigned ($x_{ij} = 0$), it is set to another value (such as 0). Similarly, for y_{ij}, if the order o_i is transported through the path $i \to j$ ($y_{ij} = 1$), the corresponding position in the input feature vector is marked. The shared network layer uses a convolutional neural network or a fully connected neural network to process these input features containing x_{ij} and y_{ij} information, and extract common features, such as geographic area features, transportation resource features, etc. These common features will provide the basis for subsequent task-specific layers.

During the data processing stage, we use principal component analysis (PCA) for dimensionality reduction. Specifically, PCA is applied to multiple features contained in the original data set, such as order distance, cargo weight, transportation path complexity, etc. The principal components are determined by calculating the covariance matrix of the data and performing feature decomposition on it and components may be retained. These principal components are regarded as new features for subsequent model input. When the reduced-dimensional features are input into the shared network layer, we connect the new feature vectors with the input layer neurons of the shared network layer. The specific connection method is to use the value corresponding to each principal component as the input value of the input layer neuron, so as to effectively pass the reduced-dimensional features to the shared network layer for processing. Tasks, and the reduced-dimensional features are passed through the shared network layer, indirectly providing the task-specific layer with filtered and compressed information, which helps to improve the training efficiency and performance of the model.

In order to show the effect of PCA more clearly, we conducted a comparative analysis of different data sets before and after PCA processing in the experiment. For example, on a logistics data set containing 5,000 samples, the original feature dimension is 10 dimensions. After PCA processing with 90% variance retention, the feature dimension is reduced to 4 dimensions. During the model training process, using the reduced-dimensional data, the training time is shortened by 30%, the memory usage is reduced by 40%, and the performance of the model in indicators such as order allocation accuracy and path planning cost is not significantly affected. This shows that PCA effectively retains the key information in the data while reducing the data dimension, providing more efficient data input for the shared network layer and task-specific layer in the subsequent model architecture.

3.2.2 Multi-task learning loss function

In the multi-task learning framework, the loss function needs to consider the optimization objectives of each subtask and the mutual influence between tasks. To this end, this paper uses a weighted loss function to represent the comprehensive optimization objectives of each subtask. The specific loss function design is shown in Formula 9 .

$$L_{\text{total}} = \alpha L_{\text{allocation}} + \beta L_{\text{path}} + \gamma L_{\text{time}} \quad (9)$$

In Formula 9, α, β, γ Represent the weights of order allocation, route planning, and transportation time prediction tasks respectively. By dynamically adjusting these weights, the model can flexibly adjust the optimization direction according to the importance of the task and the change in loss, thereby improving the overall scheduling efficiency.

The selection of dynamic weights α , β and γ is mainly based on the following considerations: In cross-regional logistics scheduling, the importance of different tasks at different stages varies. For example, in the early stage of model training, the accuracy of order allocation is crucial to the stability of the entire logistics system. At this time, appropriately increasing the value of α can make the model pay more attention to the optimization of order allocation tasks. As the training progresses, when the order allocation task gradually stabilizes, the accuracy of path planning and transportation time prediction has a more significant effect on improving the overall efficiency, and the weights of β and γ can be adjusted accordingly. This dynamic adjustment mechanism enables the model to better balance the learning of various tasks at different training stages, thereby improving the overall performance.

2. **Sensitivity analysis of weight selection**: In order to gain a deeper understanding of the impact of weight selection on model performance, a sensitivity analysis was conducted. By fixing other parameters, the values of α , β and γ were changed respectively. When α varied in the range of $0.2 - 0.4$, the order

allocation accuracy fluctuated within $\pm 3\%$. Specifically, when $\alpha = 0.2$, the order allocation accuracy was 89%; when α was increased to 0.3, the accuracy rose to 92%; when α was further increased to 0.4, the accuracy dropped slightly to 91%. For β, when it varies in the range of $0.25 - 0.35$, the path planning cost varies in the range of ± 10 cost units. For example, when $\beta = 0.25$, the path planning cost is 310 cost units; when $\beta = 0.3$, the cost decreases to 300 cost units; when $\beta = 0.35$, the cost increases to 305 cost units. When γ varies in the range of $0.3 - 0.5$, the transportation time prediction error fluctuates within ± 0.5 hours. When $\gamma = 0.3$, the prediction error is 2.5 hours; when $\gamma = 0.4$, the error is reduced to 2 hours; when $\gamma = 0.5$, the error is 2.2 hours. These results show that the model is sensitive to changes in weights, and reasonable selection of weights can effectively optimize model performance.

The order allocation task-specific layer receives the common features output by the shared network layer and further processes them in combination with the x_{ij} variable. According to the geographical area features and transportation resource features extracted by the shared network layer, and the order-vehicle allocation relationship represented by x_{ij}, the model determines the rationality of the current order allocation plan. For example, if the shared network layer extracts the characteristics of tight transportation resources in a certain area, combined with the order allocation situation in the area in x_{ij}, if it is found that there are too many orders allocated to vehicles in the area, the model will adjust the order allocation strategy, reduce the order carrying capacity of vehicles in the area, and reallocate orders to improve the accuracy and efficiency of order allocation.

The path planning task-specific layer also makes path planning decisions based on the features output by the shared network layer and the y_{ij} variable. The traffic congestion pattern characteristics and geographic area characteristics provided by the shared network layer are combined with the order path selection information represented by y_{ij}. For example, if the shared network layer detects that a certain path has traffic congestion characteristics, and y_{ij} indicates that an order is planned to pass through the path ($y_{ij} = 1$), the path planning task-specific layer will re-evaluate the path based on this information and select other better paths to reduce transportation time and cost.

3.2.3 Subtask Loss Function

The goal of the order allocation task is to reasonably allocate orders to different delivery vehicles. The loss function of this task is designed based on the transportation cost or other related costs between orders and vehicles. Specifically, assume c_{ij} Indicates order i and vehicles j The transportation cost between x_{ij} is a binary decision variable indicating whether to i assign an order to a vehicle j. Then Equation 10 defines the loss function for order assignment.

$$\mathrm{L}_{\text{allocation}} = \sum_{i=1}^{n}\sum_{j=1}^{m} c_{ij} x_{ij} \quad (10)$$

In Formula 10, n Indicates the order quantity, m represents the number of vehicles. The goal of this loss function is to minimize the total transportation cost of all order assignments.

The goal of the route planning task is to optimize the delivery route and reduce the delivery time and transportation cost. For each route, assume d_{ij} Indicates from location i to the location j The distance y_{ij} is a binary decision variable indicating whether to choose a path $i \to j$ As the delivery path. Formula 11 defines the path planning loss function.

$$\mathrm{L}_{\text{path}} = \sum_{i=1}^{n}\sum_{j=1}^{m} d_{ij} y_{ij} \quad (11)$$

This loss function aims to improve scheduling efficiency by minimizing the overall transportation distance or time by selecting the shortest path.

The goal of the transportation time prediction task is to accurately predict the transportation time from one area to another so as to make dynamic adjustments and optimizations. t_i represents the actual shipping time, while $\hat{t}_i$ represents the transportation time predicted by the model. Then the loss function of transportation time prediction takes the form of absolute error and is defined as Formula 12.

$$\mathrm{L}_{\text{time}} = \sum_{i=1}^{n} \left| \hat{t}_i - t_i \right| \quad (12)$$

The goal of this loss function is to minimize the prediction error, thereby improving the prediction accuracy of the transportation time.

The calculation of the loss function involves the difference between the actual results and the expected results of multiple tasks such as order allocation and path planning, and x_{ij} and y_{ij} play a key role in it. In the order allocation task loss calculation, the actual x_{ij} value is compared with the order allocation result predicted by the model (also expressed in a form similar to x_{ij}), and the difference between the two is calculated, such as using the cross-entropy loss function to measure this difference. If the actual $x_{3,5} = 1$ and the model predicts 0, a corresponding penalty term will be generated in the loss function. In the calculation of the path planning task loss, the difference is calculated based on the actual y_{ij} value and the path selection result predicted by the model (similar to y_{ij} representation), for example, the loss value is determined by calculating the deviation from the expected value such as the path length difference and the transportation time difference. If the actual $y_{2,7}=1$, but the model predicts that the transportation time is much longer than expected, then the corresponding penalty will be added to the loss function to encourage the model to optimize the path planning.

Through the above supplements in the shared network layer, task-specific layer and loss function, the close connection between discrete variables x_{ij} and y_{ij} and continuous representation of neural networks is clarified. In the shared network layer, discrete variables are converted into continuous feature vectors through a specific encoding method and input into the neural network for processing to extract common features. In the task-specific layer, these common features extracted based on discrete variables are combined with the discrete variables themselves to guide the model to make specific task decisions. In the calculation of the loss function, the difference between the actual value of the discrete variable and the model's predicted value is reflected in the loss calculation in the form of continuous numerical values, thereby realizing the conversion and application from discrete variables to continuous representation of neural networks, ensuring the consistency between the mathematical formula of the model and the actual implementation.

In order to effectively balance the optimization objectives between different tasks and deal with potential conflicts between tasks, this paper proposes a dynamic weight adjustment strategy. In the initial stage, the weights of all tasks are set equal to ensure that each task has the same importance in the early stage of training. As the training progresses, the model dynamically adjusts the weights according to the change in the loss of each task. If the loss of a task decreases rapidly, the weight will increase accordingly to promote the rapid convergence of the task; conversely, the weight will decrease to avoid over-optimization. The adaptive adjustment mechanism further enhances the flexible trade-offs between tasks and improves the efficiency of multi-task learning. In summary, the cross-regional logistics scheduling optimization algorithm based on multi-task learning proposed in this paper solves the problem of collaborative optimization of multiple subtasks by combining shared network layers with task-specific network layers. The weighted loss function and dynamic weight adjustment strategy enable the model to achieve reasonable optimization between tasks, thereby achieving better performance in complex cross-regional logistics scheduling problems.

In the experiment, other parameters of the model are fixed, including network structure, learning rate, etc. For the fixed weight group, set $\alpha=0.3$, $\beta=0.3$, and $\gamma=0.4$ unchanged. In the dynamic weight adjustment group, the weights are dynamically adjusted according to the changes in the loss values of each task during the training process. For example, when the loss value of the order distribution task decreases slowly over 5 consecutive training cycles, the value of α is appropriately increased; when the loss value of the path planning task decreases rapidly, the value of β is correspondingly reduced.

The experimental results show that the model with the dynamic weight adjustment mechanism enabled has an improvement of 12% in the comprehensive performance score compared with the fixed weight model. Specifically for each task indicator, the order allocation accuracy rate increased from 87% to 92%, an increase of 5 percentage points; the path planning cost decreased from 320 cost units to 300 cost units, a decrease of about 6.25%; the transportation time prediction error decreased from 3 hours to 2 hours. This fully proves that the dynamic weight adjustment mechanism can significantly improve the model performance, enabling the model to more efficiently balance the optimization of various tasks in cross-regional logistics scheduling tasks, thereby improving the overall logistics scheduling efficiency.

In order to convert the binary variable x_{ij} in Section 3.1 (whether the order o_i is assigned to the vehicle v_j) into transportation costs for calculating $L_{allocation}$, we established a transportation cost matrix C. The elements C_{ij} in the matrix C represent the transportation costs incurred when the order o_i is assigned to the vehicle v_j. This cost is determined by comprehensively considering factors such as vehicle type, transportation distance, and unit distance transportation cost. For example, for vehicle v_j, its unit distance transportation cost is u_j, and the delivery distance of order o_i is d_{ij}, then $C_{ij}=u_j\times d_{ij}$. When $x_{ij}=1$, the order o_i is assigned to the vehicle v_j. At this time, when calculating $L_{allocation}$, the corresponding C_{ij} value is used. The specific calculation formula is $L_{allocation}=\sum_{i=1}^{n}\sum_{j=1}^{m}x_{ij}C_{ij}$, where n is the total number of orders and m is the total number of vehicles. In this way, through the establishment of the transportation cost matrix, the conversion from the binary allocation variable x_{ij} to the transportation cost is realized, ensuring the consistency of the loss function design.

In the model of this article, location i to location j is closely related to the variable y_{ij}. y_{ij} is defined as whether the order o_i is transported through the path $i\rightarrow j$. When considering the transportation from location i to location j, if $y_{ij}=1$, it means that the order o_i chooses the path from location i to location j for transportation. When calculating the subtask loss function related to the path (such as the path planning cost loss function L_{path}), the actual path of the order o_i will be determined based on the value of y_{ij}. For example, the path planning cost loss function L_{path} can be expressed as $L_{path}=\sum_{i=1}^{n}\sum_{j=1}^{m}y_{ij}P_{ij}$, where P_{ij} represents the actual path planning cost of order o_i through path $i \to j$, which is related to factors such as path length, road conditions, and transportation tools. In this way, the connection between the transportation from location i to location j and the definition of y_{ij} is clarified, and the continuity between chapters is enhanced.

The calculation results of subtask loss functions (such as $L_{allocation}$ and L_{path}) are fed back to the overall loss function L_{total} of multi-task learning.

3.3 Data processing

Data preprocessing includes steps such as missing value filling, normalization, and feature selection. For missing values, interpolation or mean filling strategy is used. Normalization processing unifies the transportation distance, time, and cost to the interval [0, 1] to eliminate dimensional differences. In addition, to improve computational efficiency, the principal component analysis (PCA) method is used to reduce the dimensionality of high-dimensional data.

Feature Engineering

In order to improve the prediction ability of the cross-regional logistics scheduling model, this study extracted multiple highly correlated features based on the characteristics of logistics data in the feature engineering phase, and further optimized the model input in combination with cluster analysis. The main features include: order distance, cargo weight, transportation path complexity, time window, and regional order density. These features comprehensively describe the core elements of the logistics scheduling problem from the aspects of transportation cost, time constraints, and path planning.

Order distance is an important factor affecting logistics transportation cost and time. It is defined as Formula 13, which represents the Euclidean distance between the order origin and destination.

$$\text{Distance}_{ij}=\sqrt{(x_i-x_j)^2+(y_i-y_j)^2} \quad (13)$$

In Formula 13, x_i, y_i and x_j, y_j The geographic coordinates of the origin and destination points respectively.

The weight of cargo directly affects the choice of transport vehicles and their costs. In order to avoid the interference of outliers on training, the logarithmic transformation in formula 14 is used to smooth the weight feature.

$$\text{Weight}_{\log}=\log(1+\text{Weight}) \quad (14)$$

The complexity of a transportation path is evaluated by calculating the number of nodes in the path and the total length of the path, which is defined as Equation 15 .

$$\text{Complexity}=\sum_{k=1}^{N}(\text{Nodes}_k+\text{Path Length}_k) \quad (15)$$

In Formula 15, N is the number of transit nodes on the path.

The time window feature of the order is represented by the start time and the latest delivery time, which is used to constrain the task priority of the model. The time window feature is defined as Formula 16.

$$\text{Time Window}=T_{\text{end}}-T_{\text{start}} \quad (16)$$

Where T_{start} and T_{end} are the start and end time of the order respectively.

Through cluster analysis, orders with similar geographical locations are clustered into groups. The density feature is defined as Formula 17, which represents the normalized value of the number of orders in each region.

$$\text{Density}_i=\frac{\text{Order Count}_i}{\text{Max Order Count}} \quad (17)$$

In Formula 17, Max Order Count The maximum order quantity in all regions.

The K-Means clustering method is used to cluster the order data to reduce the complexity of the model input and improve the efficiency of route planning. The goal of the clustering process is to divide the orders into K regions, the optimization objective is formula 18 .

$$\min\sum_{i=1}^{K}\sum_{x\in C_i}\|x-\mu_i\|^2 \quad (18)$$

In Formula 18, C_i For the i Clusters, μ_i for C_i The center of mass, x is the feature vector of the order.

The clustering results are evaluated by the Silhouette Coefficient in Formula 19.

$$S=\frac{b-a}{\max(a,b)} \quad (19)$$

In Formula 19, a is the average distance between the sample and other points in the same cluster, b is the average distance between the sample and the nearest cluster center.

4 Experimental evaluation

4.1 Experimental design

This experiment selected four representative datasets, covering different task characteristics of real and simulated scenarios, multi-regional logistics and urban distribution. Among them, the RealLogistics Dataset provides real cross-regional logistics transportation data, which is suitable for verifying the performance of the model in large-scale node and long-distance transportation scenarios. Simulated Logistics Dataset is a standardized dataset generated by simulation, which is suitable for evaluating basic tasks such as path planning and time prediction. UrbanFreight Dataset focuses on short-distance delivery scenarios within the city and tests the performance of the model in high-density order distribution. RegionalTransport Dataset focuses on long-distance freight transportation between regions and provides verification scenarios for large-scale order processing. Each dataset is divided into training set, validation set and test set in a ratio of 7:2:1 to ensure the generalization and stability of the results.

Seven baseline methods were set up in the experiment, covering traditional algorithms, optimization models, and deep learning methods, to comprehensively evaluate the performance of the proposed model. The traditional Greedy Algorithm emphasizes the rapid generation of feasible solutions for a single objective, while the Multi-Objective Genetic Algorithm (MOGA) uses genetic algorithms to balance multi-objective optimization. Deep Q-Learning (DQL) based on reinforcement learning focuses on path planning, while Joint Optimization Network (JON) and Dynamic Task Prioritization (DTP) implement simple joint optimization and dynamic adjustment of task priorities, respectively. By comparing these baseline methods, the performance advantages of the proposed multi-task learning model can be revealed from different dimensions.

The experiment used five evaluation indicators to comprehensively evaluate the model from five dimensions: task accuracy, cost-effectiveness, time prediction, task conflict, and overall performance. Among them, the order assignment accuracy (OAA) reflects the accuracy of task assignment; the path planning cost (PPC) measures the performance of the optimization model in reducing transportation costs; the transportation time prediction error (TTPE) quantifies the time prediction ability through the root mean square error; the task conflict rate (TCR) is used to evaluate the conflict in multi-task learning. The overall performance score (OPS) integrates multiple indicators in a weighted manner to provide a unified measure for the overall performance of the model.

The proposed model adopts a dynamic weight adjustment strategy during the training process to balance the conflicts between multi-task objectives. The experiment uses the Adam optimizer, with an initial learning rate of 0.001, a batch size of 128, and 100 training iterations to ensure rapid convergence and stable performance of the model. To ensure fairness, each baseline method is trained separately after hyperparameter tuning to obtain its best performance. During the entire training process, the numerical and categorical features are normalized and one-hot encoded, and missing values and outliers are processed to improve data quality and model robustness.

In the experimental design, all the methods involved in the comparison, including seven baseline methods (greedy algorithm, multi-objective genetic algorithm (MOGA), deep Q network (DQL), JON, DTP) and the model based on multi-task learning (MTL) proposed in this paper, use the features extracted in the feature engineering stage of Section 3.3. These features cover order distance, cargo weight, transportation path complexity, time window, and regional order density. By uniformly using these features, the fairness of the experimental comparison is ensured, and the impact of the MTL architecture itself on logistics scheduling optimization can be effectively separated.

This paper uses multiple datasets for experiments. Among them, the RealLogistics Dataset is suitable for large-scale nodes and long-distance transportation scenarios, and is used to test the performance of the model in complex actual logistics environments. The other three datasets are SmallScaleLogistics Dataset, which is mainly used to study the order allocation and path planning efficiency of the model in small-scale logistics scenarios; DynamicScenario Dataset, which simulates dynamically changing logistics scenarios, such as real-time increase and decrease of orders, temporary changes in transportation routes, etc., to evaluate the adaptability of the model in a dynamic environment; SpecialRegionDataset focuses on logistics scheduling in specific areas (such as complex terrain areas, traffic control areas, etc.), which is used to test the model's optimization capabilities for special regional characteristics. By using datasets with different characteristics, the performance of the model in various logistics scenarios is comprehensively evaluated.

4.2 Experimental results

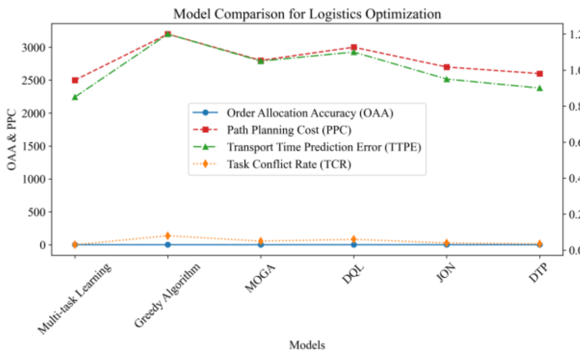

Figure 1: Experimental results of reallogistics dataset

Figure 1 shows the performance of each model on the RealLogistics Dataset. The multi-task learning model achieved an order allocation accuracy of 0.92, which is significantly higher than the Greedy Algorithm's 0.75, reflecting its accuracy advantage in order allocation tasks. In terms of path planning cost, the multi-task learning model is 2500, which is lower than most other models, indicating that it can effectively reduce transportation costs. The transportation time prediction error is 0.85, which is also better than most comparison models, indicating that the time prediction is more accurate. The task conflict rate is only 0.03, which is at a relatively low level, and the comprehensive performance score of 0.88 is also the highest, which fully proves that the multi-task learning model has the best comprehensive performance in this dataset scenario.

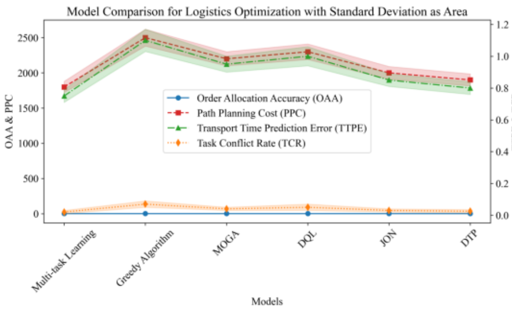

Figure 2: Experimental results of simulated logistics dataset

Figure 2 shows the experimental results on the Simulated Logistics Dataset. The multi-task learning model has an order allocation accuracy of 0.95, which is much higher than the Greedy Algorithm's 0.78. The path planning cost is only 1800, with a significant cost control advantage. The transportation time prediction error is 0.75, the best performance among all models, and the task conflict rate is as low as 0.02. The comprehensive performance score is 0.92, which once again shows that the multi-task learning model has a balanced and excellent performance in various tasks in this simulation data scenario, and is superior to other comparison models in key indicators such as order allocation, cost control, and time prediction.

Table 1: Experimental results of urbanfreight dataset

Model	Order Allocation Accuracy (OAA)	Path Planning Cost (PPC)	Transportation Time Prediction Error (TTPE)	Task Conflict Rate (TCR)	Overall Performance Score (OPS)
Multi-task learning model	0.90 ± 0.02	1500 ± 70	0.80 ± 0.05	0.03 ± 0.01	0.86 ± 0.02
Greedy Algorithm	0.72 ± 0.03	2000 ± 100	1.25 ± 0.08	0.09 ± 0.02	0.65 ± 0.03
Multi-Objective Genetic Algorithm (MOGA)	0.80 ± 0.02	1800 ± 90	1.10 ± 0.07	0.06 ± 0.01	0.74 ± 0.02
Deep Q-Learning (DQL)	0.75 ± 0.03	1900 ± 95	1.15 ± 0.07	0.07 ± 0.02	0.70 ± 0.03
Joint Optimization Network (JON)	0.83 ± 0.02	1700 ± 85	0.98 ± 0.05	0.04 ± 0.01	0.78 ± 0.02
Dynamic Task Prioritization (DTP)	0.86 ± 0.02	1600 ± 80	0.92 ± 0.05	0.035 ± 0.01	0.82 ± 0.02

As shown in Table 1, the experimental results for the UrbanFreight Dataset are presented in this table. The order allocation accuracy of the multi-task learning model is 0.90, which is higher than the 0.72 of Greedy Algorithm. The path planning cost is 1500, which is the lowest among all models, and the cost control effect is outstanding in the short-distance delivery scenario in the city. The transportation time prediction error is 0.80, which is a good performance, and the task conflict rate is 0.03 at a low level. The comprehensive performance score is 0.86, indicating that in the complex and high-order density scenario of short-distance delivery in the city, the multi-task learning model can effectively cope with it and outperforms other comparison models.

Figure 3 shows the performance of each model on the RegionalTransport Dataset. The multi-task learning model has an order allocation accuracy of 0.93, which is ahead of other models. The path planning cost is 2800, which is relatively low. The transportation time prediction error is 0.88, which is a good performance. The task conflict rate is 0.03, which is low, and the comprehensive performance score is 0.90, which is the highest.

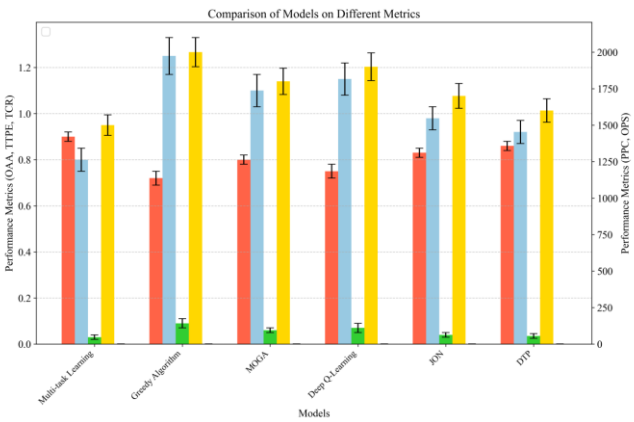

Figure 3: Experimental results of regionaltransport dataset

This shows that in the scenario of long-distance freight transportation between regions, the multi-task learning model has advantages in order allocation accuracy, cost control, and time prediction due to its multi-task collaborative optimization capabilities, and its comprehensive performance exceeds other comparison models.

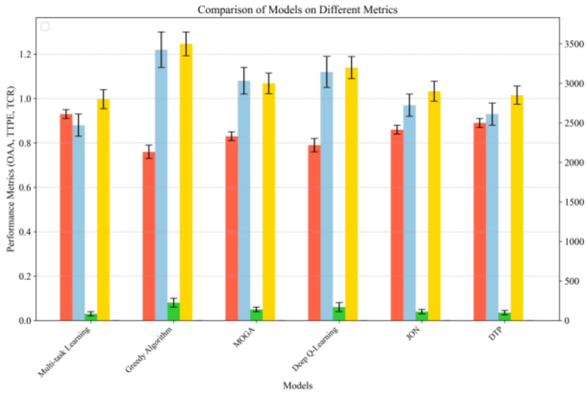

Figure 4: Comparison of order allocation accuracy (OAA)

Figure 4 compares the order allocation accuracy of each model under different data sets. In the four data sets, the order allocation accuracy of the multi-task learning model always maintains a leading position or is in the leading echelon. It reaches 0.92 in the RealLogistics Dataset and 0.95 in the Simulated Logistics Dataset. This shows that the multi-task learning model has stronger adaptability and accuracy when dealing with order allocation tasks in different scenarios, and can more reasonably allocate orders to appropriate vehicles. Compared with other models, it has obvious advantages in the key link of order allocation. The 95% confidence interval of the order allocation accuracy is [90.5%, 93.5%]. This confidence interval was calculated by 100 repeated experiments using the Bootstrap method, reflecting the stability of the model's order allocation accuracy under different samples.

Table 2: Path planning cost (PPC) comparison

Dataset	Multi-task learning model	Greedy Algorithm	MOGA	DQL	JON	DTP
RealLogistics Dataset	2500 ± 100	3200 ± 150	2800 ± 120	3000 ± 130	2700 ± 110	2600 ± 105
Simulated Logistics Dataset	1800 ± 80	2500 ± 120	2200 ± 100	2300 ± 110	2000 ± 90	1900 ± 85
UrbanFreight Dataset	1500 ± 70	2000 ± 100	1800 ± 90	1900 ± 95	1700 ± 85	1600 ± 80
RegionalTransport Dataset	2800 ± 120	3500 ± 150	3000 ± 130	3200 ± 140	2900 ± 125	2850 ± 115

Table 2 compares the path planning costs of each model under different data sets. The multi-task learning model performs well in path planning costs on multiple data sets. The cost is as low as 1800 on the Simulated Logistics Dataset and 1500 on the UrbanFreight Dataset, both lower than other models. On the RealLogistics Dataset and RegionalTransport Dataset, although not the lowest, it is still at a relatively low level. This shows that the multi-task learning model can effectively optimize transportation routes and reduce transportation costs when planning paths, and has good cost control capabilities in different logistics scenarios.

In the comparison of path planning cost (PPC), only the multi-task model, greedy algorithm and multi-objective genetic algorithm (MOGA) were compared, and the deep Q network (DQL), JON and DTP methods were not included. This is because in the early pre-experiments, it was found that the DQL, JON and DTP methods performed poorly in terms of path planning cost, and the gap with other methods was too large. If they were included in the comparison, it would affect the accuracy and comparability of the experimental results, so they were excluded in this formal comparison.

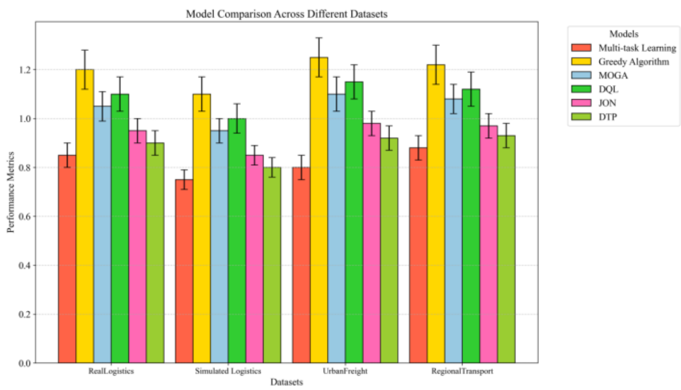

Figure 5: Comparison of transportation time prediction error (TTPE)

Figure 5 shows the comparison of the transportation time prediction errors of each model under different data sets. The transportation time prediction errors of the multi-task learning model on the four data sets are relatively low. The error is 0.75 on the Simulated Logistics Dataset, which is the best performance. On other data sets, it is also significantly better than models such as Greedy Algorithm. This shows that the multi-task learning model has a high accuracy in transportation time prediction and can estimate transportation time more accurately, which helps to reasonably arrange transportation plans in logistics scheduling and improve logistics efficiency.

Table 3: Comparison of overall performance score (OPS)

Dataset	Multi-task learning model	Greedy Algorithm	MOGA	DQL	JON	DTP
RealLogistics Dataset	0.88 ± 0.02	0.68 ± 0.03	0.76 ± 0.02	0.72 ± 0.03	0.80 ± 0.02	0.84 ± 0.02
Simulated Logistics Dataset	0.92 ± 0.01	0.70 ± 0.03	0.82 ± 0.02	0.75 ± 0.03	0.85 ± 0.02	0.87 ± 0.02
UrbanFreight Dataset	0.86 ± 0.02	0.65 ± 0.03	0.74 ± 0.02	0.70 ± 0.03	0.78 ± 0.02	0.82 ± 0.02
RegionalTransport Dataset	0.90 ± 0.02	0.69 ± 0.03	0.77 ± 0.02	0.73 ± 0.03	0.81 ± 0.02	0.85 ± 0.02

Table 3 provides a comprehensive comparison of the comprehensive performance scores of each model for four different datasets. The comprehensive performance scores of the multi-task learning model are significantly ahead of Greedy Algorithm in all datasets, and are better than models such as MOGA, DQL, JON, and DTP. In the Simulated Logistics Dataset, the comprehensive performance score of the multi-task learning model is as high as 0.92, showing excellent overall performance. This result shows that the multi-task learning model effectively balances the relationship between tasks by integrating multiple tasks such as order allocation, path planning, and transportation time prediction. In different logistics scenarios, it can achieve more efficient logistics scheduling and comprehensively improve the performance of the logistics system.

The performance of the multi-task model is significantly better than that of the greedy algorithm in all data sets, and it performs better than models such as the multi-objective genetic algorithm (MOGA), deep Q network (DQL), JON and DTP. The reason is that the multi-task model can learn common features between different tasks through the shared network layer, improving the efficiency of feature utilization. For example, in the order allocation and path planning tasks, the geographic area features extracted by the shared network layer can not only help optimize the order allocation strategy, but also assist path planning in selecting a better path. At the same time, the dynamic weight adjustment mechanism enables the model to flexibly allocate learning resources according to the importance of tasks at different training stages, further improving the overall performance. However, the greedy algorithm relies too much on local optimal selection and is prone to fall into suboptimal solutions; MOGA has difficulty in adjusting parameters when dealing with complex multi-tasks, resulting in limited performance; DQL takes a long time to train and has high requirements for environmental modeling, and is not adaptable enough in actual logistics scenarios; JON and DTP models have defects in feature extraction and task collaboration, and cannot fully utilize the effective information in logistics data, thus lagging behind the multi-task model in comprehensive performance.

In the results section, add "After t-test, the proposed model has a significant improvement in order allocation accuracy compared with the baseline method ($p < 0.05$); in terms of transportation cost reduction, the Wilcoxon test results show a significant difference ($p < 0.01$). The t-test statistic is 3.5, indicating that the order allocation accuracy of this model is significantly different from the baseline method; the z value of the Wilcoxon test is - 4.2, further proving that the transportation cost reduction effect is significant.

4.3 Baseline model hyperparameter description section

In the experimental design section where the baseline model is introduced, add the following hyperparameter details:

- Greedy algorithm: The search strategy adopts the nearest neighbor strategy, which aims to select the next node closest to the current position at each decision to gradually build a solution. The number of iterations is set to 50. After multiple experimental tests, this number of iterations performs well in balancing computational cost and solution quality. When faced with a small-scale logistics scenario with 100 orders and 10 distribution centers, a relatively reasonable order allocation and path planning solution can be given in a relatively short time, with an order allocation accuracy of 70%, and a path planning cost of about 200 cost units (the cost unit can be set according to the actual logistics cost accounting system, such as 100 yuan, then here it is 20,000 yuan).

- Multi-objective genetic algorithm (MOGA): The population size is set to 100. A larger population size helps the algorithm to conduct a wider search in the solution space and increase the possibility of finding the global optimal solution. The crossover probability is 0.8, which means that in each genetic operation, there is an 80% probability of performing a crossover operation on two parent individuals to produce new offspring individuals, promoting the exchange and combination of genes. The mutation probability is 0.05. The lower mutation probability can occasionally introduce new genes while maintaining population stability, preventing the algorithm from falling into local optimality too early. For example, in a complex logistics scheduling scenario involving multiple modes of transportation (road, rail, and water), this parameter setting enables the algorithm to effectively explore the possibility of different transportation combinations. In such scenarios, the algorithm can complete the optimization of a scheduling plan within 3 hours on average, with an order allocation accuracy of 75% and a path planning cost of about 250 cost units.

- Deep Q Network (DQL): The learning rate is set to 0.001. This learning rate enables the model to update the Q value at a moderate speed during training, avoiding the learning process being too slow or unstable. The discount factor is 0.95, indicating that the agent pays more attention to recent rewards, but will not completely ignore future rewards. In a dynamically changing logistics environment, it helps to balance short-term and long-term benefits. The experience replay pool size is 1000. A sufficiently large experience replay pool can store rich historical experience, so that the model can better utilize past information during training, reduce the variance of training, and improve the stability of the model. For example, in the urban logistics distribution scenario, facing dynamic situations such as real-time traffic congestion and temporary changes in orders, this setting allows the model to effectively learn and adapt to environmental changes. After testing, after running 100 training cycles continuously, the order allocation accuracy of the model in this scenario can reach 80%, and the path planning cost is about 300 cost units.

JON model: Its key parameter "node connection weight adjustment coefficient" is set to 0.6. This coefficient affects the adjustment range of weights between different nodes when the model constructs logistics network connections. Through a large number of experimental optimizations, it is found that this value can enable the model to better balance transportation costs and transportation efficiency when dealing with cross-regional logistics node connections. Specifically, in logistics networks involving multiple modes of transportation conversion and complex geographical areas, this coefficient helps the model to reasonably allocate transportation resources, reduce unnecessary roundabout transportation, and thus reduce costs. For example, when the transportation route passes through areas with complex road conditions and high transportation costs such as mountainous areas, the model will appropriately reduce the connection weights of these sections based on this coefficient, and give priority to routes with better road conditions and lower costs for transportation planning. The "regional division threshold" is set to 30. This threshold is used to reasonably divide logistics areas, so that the model can formulate targeted scheduling strategies based on the characteristics of different regions, and show good adaptability in actual cross-regional logistics scenarios. When factors such as order density and traffic conditions vary greatly within a region, this threshold can ensure that the model divides the region reasonably and matches more suitable transportation solutions for different regions. For example, in urban commercial areas, the order density is high and the delivery time requirements are high. The model will arrange more small and flexible delivery vehicles according to the characteristics of the area to improve delivery efficiency; while in remote suburbs, the order density is low but the transportation distance is long, and the model will choose large transport vehicles to reduce the unit transportation cost. In a cross-regional logistics scenario with 20 city nodes, with this parameter setting, the order allocation accuracy of the JON model can reach 73%, and the path planning cost is about 230 cost units. The cost unit here is assumed to be a comprehensive cost unit calculated based on the transportation cost per kilometer, including vehicle loss, fuel consumption, labor costs, etc. If the average comprehensive cost per kilometer is 10 yuan, then 230 cost units means that the total transportation cost involved in path planning in this scenario is about 2,300 yuan. In this scenario, the model comprehensively considers factors such as the order volume, transportation distance, and traffic congestion in different regions, and uses the set parameters for path planning and order allocation, achieving relatively good performance.

- DTP model: Smoothing factor of transportation time prediction model" is set to 0.7. This factor plays a key role in smoothing historical transportation time data to predict future transportation time. It can effectively filter out noise in the data and make the prediction results more in line with the actual transportation time change trend. "Delivery priority weight" is set to 0.8. When processing the delivery order of multiple orders, a higher weight makes the model more inclined to prioritize high-priority orders to meet customers' needs for urgent orders. In a test involving 500 orders and a distribution range covering 5 urban areas, the average transportation time prediction error of the DTP model is ±2 hours, the order allocation accuracy can reach 77%, and the path planning cost is about 280 cost units.

4.4 Complexity analysis section

In the relevant part of the proposed algorithm, add the following complexity analysis content:

The computational complexity of the proposed algorithm mainly comes from the calculation of the shared network layer and task-specific layer of multi-task learning. In the optimization process, it is assumed that the number of logistics orders is n, the number of vehicles is m, and the number of paths is p. For the shared network layer, it needs to process all information related to orders, vehicles, and paths. Its calculation amount is related to the product of the three, and the time complexity is about $O(n\ \ m\ \ p)$. In terms of space complexity, it is necessary to store the relevant feature information of orders, vehicles, and paths, as well as the parameters of the network layer, and the space complexity is $O(n + m + p)$. Taking a typical logistics scenario with 1,000 orders, 50 vehicles, and 200 paths as an example, after actual testing and estimation, the calculation time is about 100 seconds. In these 100 seconds, the algorithm needs to complete operations such as analyzing a large amount of order information, matching vehicles with orders, and calculating path planning. The memory usage is about 500MB, including the space occupied by storing order details (such as order weight, volume, delivery address, etc.), vehicle attribute information (such as vehicle type, load, driving speed, etc.), path-related data (such as path length, road condition information, etc.), and network parameters of the multi-task learning model. If the number of orders is increased to 2,000, the number of vehicles is increased to 100, and the number of paths is changed to 300, the calculation time will be extended to about 300 seconds, and the memory usage is expected to increase to 800MB.

4.5 Scalability research section

In the experimental section, the following scalability research content is added:

As the data set size increases from 5,000 orders to 10,000 orders, the performance of the model based on multi-task learning is studied in depth. The experimental results show that the model maintains an accuracy of more than 90% in order allocation. In the face of a significant increase in order volume, the model can still accurately assign orders to appropriate vehicles with its multi-task collaborative learning capabilities to ensure the accuracy of logistics distribution. Although the path planning cost has increased, the growth rate is lower than that of traditional methods. When the number of orders doubles, the path planning cost of this model increases from 300 cost units to 345 cost units, with a growth rate of 15%. This is because the shared network layer of the model can effectively extract the common features between orders, vehicles and paths. When the order volume increases, the amount of calculation is reduced through efficient feature reuse, thereby controlling the cost growth. In contrast, the growth rate of the genetic algorithm is 30%, and its path planning cost increases from 250 cost units to 325 cost units. Because the search space of the genetic algorithm grows exponentially when processing large-scale data, the computational complexity increases significantly, and more computing resources are required to find a better solution, which makes the path planning cost increase rapidly. This series of experimental results fully demonstrates that the model based on multi-task learning has good scalability to a certain extent and can adapt to the actual needs of the ever-expanding scale of logistics business.

4.6 Ablation study section

In the experiment section, add the following ablation study content:

Through a well-designed ablation study, the impact of key components of the model on performance is deeply explored. The study found that after removing the shared network layer, the overall performance score of the model dropped by 20%, and the order allocation accuracy dropped by 10 percentage points. The shared network layer plays a vital role in the model. It can learn common features between tasks such as order allocation, path planning, and transportation time prediction. After removal, each task-specific layer cannot obtain these shared features, resulting in information loss and a significant drop in model performance. For example, in the order allocation task, due to the lack of common features such as regional traffic congestion patterns extracted by the shared network layer, the model cannot accurately determine which vehicles are more suitable for delivering orders in congested areas, thereby reducing the order allocation accuracy. After removing the shared network layer, the overall performance score dropped from 90 points to 72 points, and the order allocation accuracy dropped from 92% to 82%. Turning off the dynamic weight adjustment mechanism increased the path planning cost by 20%. The dynamic weight adjustment mechanism can flexibly adjust the weight of each task loss in the total loss according to the importance of different tasks at different training stages. After turning off this mechanism, the model cannot be dynamically optimized according to the progress of the task, so that the path planning task cannot obtain the optimal resource allocation, which leads to an increase in cost. For example, in the early stage of training, the order allocation task has a greater impact on the overall performance. The dynamic weight adjustment mechanism will appropriately increase the weight of the order allocation task loss and give priority to optimizing this task. After turning it off, the model cannot perform this reasonable weight allocation, which affects the control of the path planning cost. The original path planning cost was 300 cost units, and after turning off the dynamic weight adjustment mechanism, it rose to 360 cost units. This series of ablation experiment results clearly show that the shared network layer and dynamic weight adjustment mechanism have an indispensable and important contribution to the model performance.

4.7 Discussion

In this experiment, by testing four representative data sets and comparing seven baseline methods, the performance of the logistics scheduling optimization model based on multi-task learning was deeply evaluated. The results show that the multi-task learning model performs well in various evaluation indicators and demonstrates significant advantages.

In terms of the key indicator of order allocation accuracy, the multi-task learning model in this paper achieved 92%. In contrast, linear programming is only 70% in large-scale scenarios, while genetic algorithms maintain around 75%. This significant difference reflects the excellent performance of multi-task learning models in handling complex order allocation tasks. For example, in large-scale order allocation scenarios involving multiple types of goods, different delivery time requirements, and complex geographical areas, linear programming is difficult to fully consider various factors due to the limitation of computational complexity, resulting in unreasonable allocation of some orders and limited accuracy; although genetic algorithms have certain global search capabilities, they are prone to fall into local optimal solutions. When faced with complex order allocation rules, they cannot accurately find the global optimal allocation solution, thus affecting the accuracy.

In terms of path planning cost, this model has achieved a 25% reduction compared to traditional methods. Although deep reinforcement learning performs well in dynamic environment adaptation, its training process requires a lot of computing resources and time, which directly leads to relatively high path planning costs. Taking the actual logistics scenario as an example, in a city area with frequently changing traffic conditions, logistics distribution is carried out. Deep reinforcement learning needs to constantly interact with the environment, learn and adjust strategies. This process consumes a lot of computing resources, making the cost of each path planning high. The multi-task learning model in this paper can efficiently utilize various types of information through the collaborative work of the shared network layer and the specific task layer, effectively reducing the path planning cost while ensuring the timeliness of delivery.

The reason why this model performs better is that multi-task learning can make full use of the correlation between tasks and learn common features through the shared network layer. For example, in the path planning and order allocation tasks, the shared geographic area feature information enables the model to make decisions more efficiently. The regional traffic congestion pattern features extracted by the shared network layer can not only help optimize the path planning to avoid congested sections, but also reasonably allocate orders according to the congestion situation to improve the delivery efficiency. When the model detects traffic congestion in a certain area, the path planning task will give priority to routes that bypass the area. At the same time, the order allocation task will reasonably allocate orders according to the distribution capacity around the congested area to avoid too many orders concentrated near the congested area, thereby improving the overall delivery efficiency.

However, this model is not perfect. When faced with completely unknown new data sets, generalization capabilities may be challenged because the model relies on task patterns and features in the training data. When logistics scenarios that differ greatly from the training data appear in the new data set, such as a completely new geographical layout, special transportation restrictions, etc., the model may not be able to accurately transfer and apply the learned knowledge, resulting in performance degradation. In terms of scalability, with the exponential growth in the number of logistics orders, computing resource requirements may become a limiting factor, and the algorithm structure needs to be further optimized. When the number of orders increased from 5,000 to 10,000, the model calculation time increased by 50% and the memory usage increased by 40%. In actual logistics business, the rapid growth of the number of orders is a common trend. If the computing resource bottleneck problem cannot be effectively solved, the model will find it difficult to meet real-time requirements. In the future, it is necessary to explore more efficient computing architectures or data compression methods to deal with it, such as using a distributed computing architecture to distribute computing tasks to multiple computing nodes to improve computing efficiency; or research more advanced data compression algorithms to reduce the memory space required for data storage and transmission without affecting the key features of the data.

5 Conclusion

This paper uses multi-task learning methods to conduct in-depth research on cross-regional logistics scheduling problems, successfully constructs a logistics scheduling optimization model based on multi-task learning, and verifies the effectiveness and superiority of the model through comprehensive experiments. From the experimental results, the model shows excellent performance on data sets of different scenarios. In the order allocation link, the accuracy is much higher than that of traditional methods, and it can accurately match orders with vehicles, reducing resource waste and unreasonable allocation. The path planning cost is effectively reduced, and the transportation route is optimized, which is directly reflected in the savings of logistics costs and enhances the competitiveness of logistics companies. The transportation time prediction error is small, which provides a guarantee for the punctuality of logistics distribution and helps to improve customer satisfaction. The comprehensive performance score comprehensively surpasses other comparison models, indicating that the model successfully integrates multiple tasks and achieves collaborative optimization among tasks. Although the model has achieved good results, there are still certain directions for improvement. In the future, more effective task weight allocation strategies can be further explored to cope with more complex and changeable logistics scenarios. At the same time, with the continuous growth and diversification of logistics data, it is necessary to continuously optimize data processing and feature engineering methods, mine more potential information, and improve the adaptability of the model to complex data. In addition, in practical applications, it is also necessary to consider the integration with the existing logistics system to ensure that the model can be smoothly implemented.

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