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Intelligent Logistics Scheduling Algorithm in Dynamic Traffic Environment

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With the increasingly heavy traffic conditions, the dynamic traffic environment has gradually become a serious problem for the scheduling of logistics vehicle transportation. Traditional heuristic scheduling algorithms are mostly based on static scheduling, lacking adaptability to dynamic environments that involve, for instance, traffic accidents and natural disasters, and failing to fully consider multiple issues such as cost and time for optimization, resulting in low scheduling efficiency. This study used the multi-objective optimization of MAPPO (Multi-Agent Proximal Policy Optimization) and the dynamic information extraction advantages of LSTM (Long Short-term Memory) to study intelligent logistics scheduling under dynamic traffic environments. First, the study matched the traffic monitoring data and Google maps API (Application Programming Interface) data of similar time with the logistics distribution data according to the timestamp, and combined the geocoding of the Geopy library to match the geographic location and records according to the nearest matching method. Subsequently, a mapping relationship between traffic section ID and delivery route section was established, and urban traffic system data and real-time traffic data were linked to each delivery record. Then, the LSTM model was used to capture the dynamic information of the traffic environment, generate predicted traffic flow and congestion conditions, and finally input the traffic flow, speed and other states predicted by LSTM into the MAPPO algorithm model to assist the logistics vehicle intelligent body to dynamically adjust route selection and other scheduling according to traffic conditions. The experiment was based on data from the urban traffic system of the Shenzhen Traffic Management Center and a logistics center from June to December 2023, and intelligently dispatched logistics vehicles in a dynamic environment. The results showed that in peak traffic flow, the dispatch efficiency of MAPPO-LSTM reached 87.5%, an increase of 3.5% compared to the MAPPO algorithm. The overall satisfaction score reached a high 14 points. Experiments show that the MAPPO-LSTM algorithm has good adaptability to dynamic traffic environments, greatly improves scheduling efficiency, and provides efficient guarantees for intelligent logistics transportation.

Keywords: dynamic traffic environment, intelligent logistics scheduling, MAPPO algorithm, LSTM model, scheduling efficiency

1. INTRODUCTION

With the acceleration of urbanization and the rapid development of e-commerce, the demand for logistics and transportation is increasing, and the traffic environment is becoming increasingly complex [1–2]. As a result, traditional logistics scheduling methods face severe challenges, especially in a dynamic traffic environment [3–4] where traffic accidents, natural disasters and other emergencies occur frequently, bringing huge uncertainty to logistics scheduling. At present, most scheduling algorithms are based on static scheduling and lack timely response to dynamic changes, resulting in low scheduling efficiency and affecting the overall quality of logistics services. The development of intelligent logistics scheduling algorithms that adapt to dynamic traffic environments has become an urgent goal and is necessary for improving logistics services.

In a dynamic traffic environment, efficient intelligent logistics scheduling algorithms are essential. These can help logistics systems to adapt in real time to traffic fluctuations, emergencies and extreme weather, minimize transportation delays, optimize routes and resource allocation, and reduce operating costs significantly. Efficient intelligent logistics

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scheduling algorithms use fast response and intelligent decision-making to improve logistics efficiency, meet customer expectations for punctuality and flexibility, enhance customer satisfaction, and thus improve brand competitiveness and market benefits, allowing logistics companies to maintain efficient operations and service levels in difficult environments.

The purpose of this study is to explore an efficient intelligent logistics scheduling algorithm to cope with the dynamic traffic environments that can present challenges to logistics transportation. The study combines the MAPPO algorithm in multi-agent reinforcement learning and the LSTM model to establish accurate real-time traffic status mapping by collecting and organizing traffic monitoring data and logistics distribution data. The LSTM model is used to capture the dynamic characteristics of traffic flow and congestion, and the prediction results are integrated into the MAPPO algorithm to optimize the scheduling strategy of logistics vehicles. The experiment verifies the scheduling efficiency of the MAPPO-LSTM algorithm, significantly improves its scheduling performance, and proves its effectiveness and adaptability in dynamic environments.

The paper makes the following contributions to the field of logistics scheduling:

(1) The study combines the MAPPO algorithm in multi-agent reinforcement learning with the LSTM model and applies it to intelligent logistics scheduling, effectively improving the adaptability to complex situations in dynamic traffic environments.

(2) The experiment involves the LSTM model and makes full use of its ability to capture dynamic features to predict traffic flow and congestion in real time, so that the MAPPO algorithm can provide more scientific scheduling decisions for logistics vehicles, significantly improving scheduling efficiency and reliability.

(3) The study verifies the effectiveness of the MAPPO-LSTM algorithm in a dynamic environment through an empirical study of data from Shenzhen's transportation system and logistics center in 2023, providing an important reference and practical basis for subsequent related research, and promoting the application and development of intelligent logistics scheduling technology.

2. RELATED WORK

In the field of intelligent logistics scheduling, many researchers have begun to study scheduling problems under dynamic traffic environments and have achieved a lot of research results. Lei [5], He [6] and other scholars used the information interaction technology in the Internet of Things technology and combined it with genetic algorithms to establish a transportation logistics scheduling model to reduce the time of logistics transportation. Integer programming [7–8] and mixed integer linear programming models [9–11] are widely used for logistics scheduling as they improve scheduling efficiency. However, these models do not take the dynamic traffic environment into account. Scheduling strategies in dynamic environments include robust scheduling [12], pre-reactive scheduling [13] and fully reactive scheduling [14]. In fully reactive scheduling, heuristic algorithms, genetic algorithms [15–16], simulated annealing algorithms [17], and ant colony algorithms [18–19] are widely used in intelligent transportation and logistics scheduling, and have solved dynamic problems to a certain extent. However, they are all designed based on specific dynamic scenarios and lack adaptive adjustment capabilities. The aforementioned researchers have achieved some optimization of transportation and logistics scheduling efficiency using heuristic algorithms, but they still lack strong adaptability in dynamic environments.

With the rapid development of society, intelligent logistics scheduling has gradually tended to scheduling optimization with multiple objectives. Wu et al. used a multi-objective ant colony system method based on multiple groups to schedule cold chain logistics, comprehensively considering quality loss, personnel and vehicle costs, and transportation costs to achieve a good balance [20]. Ding et al. used a combination of genetic algorithm and gray interval to intelligently schedule emergency logistics at multiple supply and demand points, ensuring good supply at each demand point [21]. These researchers used the multi-objective ant colony system method and genetic algorithm to perform multi-objective scheduling of logistics and improve the quality of comprehensive logistics services. However, there is still insufficient consideration of multi-objective optimization, resulting in the failure to effectively improve service quality and customer satisfaction.

In recent years, many scholars have begun to combine deep learning with reinforcement learning to improve the intelligence level of scheduling systems. Sun [22] and Guo et al. [23] applied the LSTM algorithm to scheduling in manufacturing and to item transmission, extracting dynamic change information and greatly improving the ability to capture dynamic information. For multi-objective optimization, Li et al. used the Q-learning algorithm to schedule AGV (Automated Guided Vehicle) in logistics warehouses, meeting the scheduling requirements, but it is applicable only to small-scale scheduling [24]. Ai et al. used the Double DQN (Deep Q-Network) algorithm to further improve the efficiency of bulk cargo terminal logistics scheduling, thereby reducing operating costs and improving scheduling efficiency [25]. It can be seen that the LSTM algorithm applied in this paper is effective and can effectively extract dynamic logistics information. Previous scholars used reinforcement learning algorithms such as DQN and Q-learning algorithms for multi-objective optimization, but they are all based on independent intelligent agents, lack sufficient mutual cooperation, and have poor response capabilities in terms of dynamic arrival.

3. PROBLEM DESCRIPTION AND MODELING

3.1 Problem Description

Transportation logistics scheduling involves the planning of suitable delivery routes for multiple loading and unloading points to ensure that several logistics vehicles can achieve

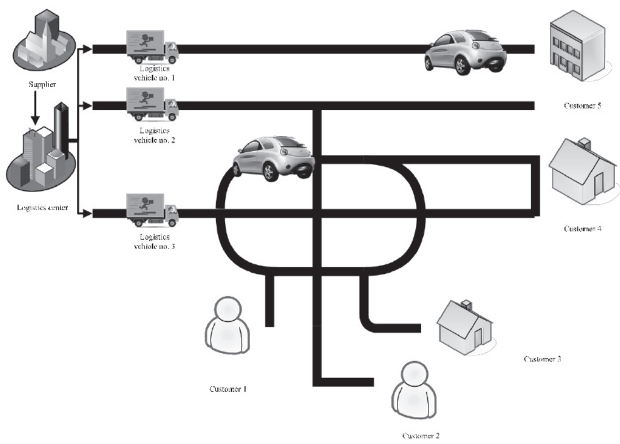

Figure 1 Schematic diagram of intelligent transportation logistics scheduling.

distribution tasks in an orderly manner. In logistics scheduling, congestion and overlap cannot occur between logistics vehicles. From the perspective of graph theory, the transportation logistics scheduling problem is a completely undirected graph connection problem, where v represents the location of the distribution center and other vertices represent the locations of customers who need to be served [26]. The set of line segments represent the real-time route of the delivery task, where the initial vertex represents the logistics distribution center. After a logistics vehicle completes a delivery task, the destination of the previous delivery corresponds to the starting point of the next delivery task.

Traditional scheduling methods are based mostly on static models and do not consider the dynamic changes in the traffic environment. Factors such as traffic flow fluctuations, accidents, construction and bad weather can change transportation routes and times significantly. To address this problem, this study integrates multiple data sources, including traffic monitoring cameras, GPS (Global Positioning System) and real-time traffic information API, to collect data such as traffic flow, speed and accident information in real time, and to predict future traffic conditions.

In intelligent transportation logistics scheduling, multi-objective optimization is an important means of resolving scheduling conflicts. If customers have strict requirements for timely delivery of products, this can lead to constraint problems in target optimization. If the delivery time is shortened by optimizing the collaborative production or transportation time between enterprises, it can increase inventory costs at some stages and make it difficult to meet customers' expected delivery time. How to balance the relationship between logistics scheduling transportation costs, time, customer satisfaction, etc., is an important constraint factor in transportation logistics scheduling.

The schematic diagram of intelligent transportation logistics scheduling is shown in Figure 1.

As shown in Figure 1, first, the logistics center picks up the goods from the supplier, and then distributes the goods to each logistics vehicle for delivery to ensure that the goods are delivered to the customer's home on time. During the entire delivery process, the logistics center uses the scheduling algorithm to intelligently schedule logistics vehicles.

3.2 Mathematical Model Establishment

3.2.1 Establishment of Objective Function

For the intelligent logistics scheduling problem under dynamic traffic environment, a mathematical model is established to comprehensively consider transportation cost, delivery time and customer satisfaction. The objective function formula (1) is:

$$Z = \alpha_1 \cdot A + \alpha_2 \cdot B + \alpha_3(1 - C) \tag{1}$$

where Z represents the comprehensive optimization goal, A represents the transportation cost, B represents the delivery time, and C represents customer satisfaction.

Formula 2 is used to calculate the transportation cost:

$$A = \sum_{i=1}^{n} \sum_{j=1}^{m} a_{ij} \cdot \beta_{ij} \tag{2}$$

where a_{ij} represents the transportation cost from supplier to customer. β_{ij} represents the scheduling decision variable, corresponding to whether to select the path.

The delivery time is calculated with formula (3):

$$B = \sum_{i=1}^{n} \sum_{j=1}^{m} b_{ij} \cdot \beta_{ij} \tag{3}$$

where b_{ij} represents the estimated delivery time from supplier to customer.

Customer satisfaction is measured by the timeliness of delivery and service quality, and is calculated with formula (4):

$$C = \frac{1}{m} \sum_{j=1}^{m} c_j \tag{4}$$

where c_j represents the customer satisfaction score.

3.2.2 Constraint Setting

In order to ensure the feasibility of the scheduling model, the constraints are set as follows.

(1) Supplier satisfaction constraint

For supplier satisfaction, it is measured by the maximum number of tasks that can be executed by the supplier and the actual number assigned to the supplier, as shown in formula (5) [27]:

$$Y_1^*(j) = \frac{g(y_{it)}}{m\gamma_m} \tag{5}$$

where γ_m represents the maximum number of tasks that the supplier can actually accept.

At different times, the supplier can estimate the task completion capability based on the actual work situation. This paper sets a task allocation coefficient and a penalty coefficient to ensure the supplier's satisfaction, as shown in formula (6):

$$Y^{**}(j) = \begin{cases} \frac{\gamma_{it}}{Y_1^*\gamma_m} l_i\gamma_{it} < y_{it} < \gamma_m \\ \frac{Y_1^*\gamma_m}{\gamma_{it}}\gamma_{it}^- < y_{it} < \gamma_{it} \\ \frac{\gamma_{it}^-}{\gamma_{it}} 0 < y_{it} < \gamma_{it}^- \end{cases} \tag{6}$$

where γ_{it}^- represents the task allocation coefficient and l_i represents the penalty coefficient.

In logistics services, in order to further measure the supplier's satisfaction, the logistics level is used for comprehensive evaluation, and is calculated with formula (7):

$$Y_1(j) = \begin{cases} \eta_i + \theta_{it} - \vartheta_{it} & t = 1 \\ Y^{**}(j) - y_{it} + y_{i(t-1)} + \theta_{it} - \vartheta_{it} & otherwise \end{cases} \tag{7}$$

The range of i corresponds to 1 to n, and ϑ_{it} represents the loss of logistics capacity. η_i represents the number of services provided by the supplier during the waiting period, and θ_{it} represents the number of additional services provided during the waiting period.

(2) Transportation cost constraint

The transportation cost a_{ij} of the logistics vehicle is expressed with formula (8):

$$\begin{cases} a_{ij} = Dd_{ij} + Ee_{ij} + Ff_{ij} \\ a_{ij} \leq a_{ijm} \end{cases} \tag{8}$$

where Ff_{ij} represents fuel consumption cost, Ee_{ij} represents toll cost, and Dd_{ij} represents wear cost. a_{ijm} represents the maximum transportation cost.

The constraint coefficient of transportation cost is obtained with formula (9):

$$Y_2(j) = \begin{cases} \frac{a_{ij}}{a_{ijm}}, a_{ij} \leq a_{ijm} \\ 0, a_{ij} > a_{ijm} \end{cases} \tag{9}$$

(3) Transportation time constraint

In transportation logistics scheduling, the coefficient of transportation time is given with formula (10).

$$Y_3(j) = \begin{cases} \frac{b_{ij}}{b_{ijm}}, b_{ij} \leq b_{ijm} \\ 0, b_{ij} > b_{ijm} \end{cases} \tag{10}$$

where b_{ijm} represents the estimated maximum time of logistics vehicle transportation.

(4) Vehicle load capacity and maximum transportation distance constraints

For different logistics vehicles, there can be some differences in their load capacity and transportation distance. The vehicle load capacity and maximum transportation distance constraint coefficients are shown in formula (11).

$$Y_4(j) = \begin{cases} \sum_{j\in J} \beta_{ij}\delta_j \leq O \\ \sum_{i\in I}\sum_{j\in J} y_{ij}\zeta_{ij} \leq P \end{cases} \tag{11}$$

where O represents the payload of the logistics vehicle, and P represents the maximum transportation distance. δ_j represents the commodity demand at the target distribution point.

The mathematical model of comprehensive transportation logistics dynamic scheduling is expressed with formula (12).

$$Y(j) = \iota_1 Y_1(j) + \iota_2 Y_2(j) + \iota_3 Y_3(j) + \iota_4 Y_4(j) \tag{12}$$

where ι_1, ι_2, ι_3, and ι_4 represent the weights corresponding to the supplier's satisfaction constraint, transportation cost, transportation time, logistics vehicle load capacity, and maximum delivery distance, respectively.

4. MODEL SOLUTION BASED ON MAPPO ALGORITHM AND CONSTRUCTION OF LSTM MODEL

Based on the established mathematical model, this study combines the MAPPO algorithm model and the LSTM model to perform intelligent logistics scheduling in a dynamic traffic environment to ensure the delivery of goods. The MAPPO-LSTM model structure is shown in Figure 2.

In Figure 2, the blue lines represent the interaction paths between logistics vehicles, and the black lines represent the fusion paths of dynamic information. As can be seen from Figure 2, each logistics vehicle agent corresponds to a scheduling strategy block, in which multiple logistics vehicle agents are sequentially scheduled by means of a dynamic scheduling mechanism, and interact with dynamic exchanges in real time to output the optimal scheduling strategy. In the MAPPO-LSTM model structure, multiple agents share a global Critic network and LSTM dynamic information processing module network.

4.1 MAPPO Scheduling Algorithm

The basic framework of MAPPO consists of multiple agents, each of which represents a logistics vehicle. Each agent performs scheduling in the environment by selecting different actions, with the goal of maximizing their respective cumulative rewards [28–29]. The MAPPO algorithm is a variant of the PPO algorithm in a multi-agent environment. It adopts an Actor-Critic architecture and learns a centralized value function in the Critic network to ensure the convergence and sample complexity of the algorithm.

In the MAPPO algorithm, the loss function and weight update method of each logistics vehicle agent are different, and the Actor network and the Critic network are independent. The training process of the MAPPO algorithm [30] is as follows:

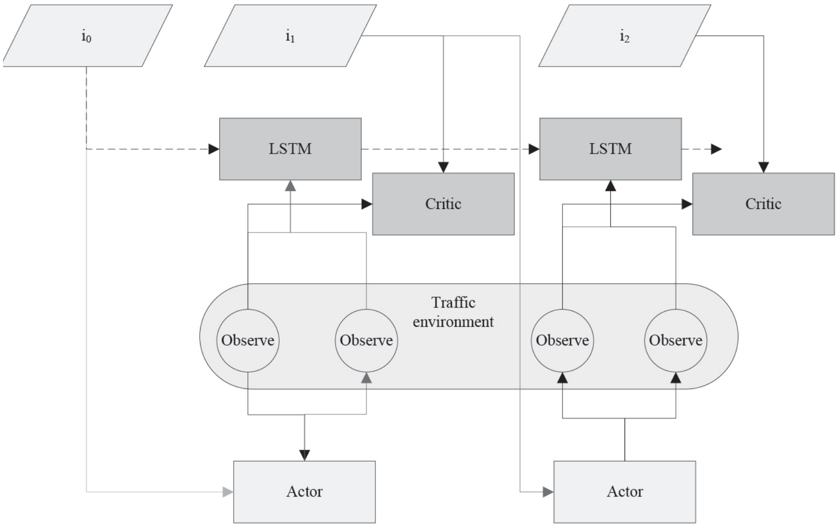

Figure 2 MAPPO-LSTM model structure.

(1) The Critic network is used to calculate the state value and discounted reward, the advantage function, and the weight of the Critic network is updated.

(2) Based on the Actor network, the environment is interacted with and information is output to the experience pool.

(3) The importance sampling rate is calculated and the weight of the Actor network is updated.

(4) Based on the interactive fusion of data and environment, the advantage function is calculated in combination with information on the environmental state to output the optimal dynamic scheduling strategy.

In the Critic network, a sequence is first extracted from the experience sample, and the target value function is output using temporal differential privacy. Based on the output target value function, the forward propagation mechanism is used to calculate the value function of the current state, and the policy parameter gradient in the Critic network is updated. The sequence is expressed as (s_t, s_{t+1}, k_t, r_t).

The target value function is calculated with formula (13):

$$h_t = q_t + \lambda U(s_{t+1};\mu) \tag{13}$$

where h_t represents the target value function, μ represents the weight corresponding to the Critic network, and q_t represents the reward value.

The loss function is calculated with formula (14):

$$V(\mu) = E[h_t - U(s_t;\mu)]^2 \tag{14}$$

where $V(\mu)$ represents the loss function and $U(s_t;\mu)$ represents the output of the Critic network.

The gradient update of the policy parameters in the Critic network is expressed with formula (15):

$$\mu \leftarrow \mu - \rho \nabla V(\mu) \tag{15}$$

where ρ represents the learning rate and ∇ represents the gradient calculation function.

The Actor network uses the optimization function to update the network weights and adopts the advantage function to guide the policy network by strengthening the advantage action. The value expression of the MAPPO algorithm after taking the strategy and action is shown in formula (16).

$$W(s_t, k_t) = E(r_t | s_t = s, a_t = a;\partial) \tag{16}$$

where ∂ represents the strategy, s_t represents the state, and k_t represents the action.

The expected value, advantage function, and loss function after executing the strategy ∂ in the current state are expressed as shown in formula (17):

$$\begin{gathered} U(s) = E(r_t | s_t = s;\partial) \\ \varsigma(s_t, k_t) = W(s_t, k_t) - U(s) \\ \tau(\phi) = \max_{\phi} E_t \left\{ \left[\min \left[\frac{\partial_{\phi n}(k_t|s_t)}{\partial_{\phi o}(k_t|s_t)} \right] W(s_t, k_t), \right. \right. \\ \left. \left. \text{clip}\left(\frac{\partial_{\phi n}(k_t|s_t)}{\partial_{\phi o}(k_t|s_t)},\ 1-\varepsilon,\ 1+\varepsilon \right) W(s_t, k_t) \right] \right\} \end{gathered} \tag{17}$$

where clip represents the truncation function, $1 - \varepsilon$ and $1 + \varepsilon$ represent the intervals of policy changes. $U(s)$ represents the expected value after executing policy ∂ in the current state, $\varsigma(s_t, k_t)$ represents the advantage function, and $\tau(\rho)$ represents the loss function. ϕ represents the weight corresponding to the Actor network.

The policy network parameter update expression is shown in formula (18):

$$\Phi \leftarrow \Phi + \psi \nabla_{\phi} \tau(\phi) \tag{18}$$

where ψ represents the learning rate.

4.2 Establishment of the Scheduling State Space

In intelligent logistics scheduling under dynamic traffic environment, the establishment of the state space is crucial. Each state represents a specific configuration in the logistics system, including the current location of the logistics vehicle, task queue, traffic conditions and other information. The definition of the state variable is shown in expression (19).

$$S_t = \{Po_t, Ta_t, Ch_t\} \tag{19}$$

where Po_t represents the current location set of logistics vehicles, corresponding to the coordinate information of logistics vehicles in time t. Ta_t represents the task queue, corresponding to the unprocessed delivery tasks and status. Ch_t represents the traffic conditions, corresponding to data such as traffic flow, speed and accidents.

The definition of the state vector s is shown in formula (20).

$$s = [x_1, y_1, di_1, \ldots, x_n, y_n, di_n] \tag{20}$$

where x_1 and y_1 represent the coordinates of the logistics vehicle, and di_n represents the estimated delivery time associated with the corresponding distribution task.

4.3 Establishment of Scheduling Action Space

The definition of the action space is shown in formula (21).

$$K_t = \{k_1, k_2, ..., k_n\} \tag{21}$$

where k_n represents a scheduling decision.

The formula of the action vector k is shown in formula (22).

$$k = k_{assign} + k_{route} + k_{speed} + k_{wait} + k_{reschedule} \tag{22}$$

where k_{assign} means assigning the delivery task to a specific logistics vehicle, and k_{route} means selecting the driving path of the current vehicle. k_{wait} and $k_{reschedule}$ represent the waiting action and the rescheduling action respectively. k_{speed} represents the speed adjustment action.

4.4 Establishment of Scheduling Reward Function

In intelligent logistics scheduling, the design of the reward function is the key to the success of the reinforcement learning algorithm. The design of the reward function is successful if it can effectively reflect the contribution of scheduling strategy to the goal.

The expression of comprehensive reward function is shown in formula (23).

$$R_t = \omega_A \cdot R_A + \omega_B \cdot R_B + \omega_C \cdot R_C \tag{23}$$

where R_A, R_B, and R_C represent the rewards related to transportation cost, delivery time, and customer satisfaction, respectively. ω_A, ω_B, and ω_C represent the corresponding weight parameters.

The expression of the reward function for transportation cost, delivery time, and customer satisfaction is shown in formula (24).

$$\begin{gathered} R_A = -\pi \cdot A_t \\ R_B = \begin{cases} \pi_1 \cdot (B_i - T_{ij}) & T_{ij} \leq B_i \\ -\pi_2 \cdot (T_{ij} - B) & T_{ij} > B_i \end{cases} \quad R_C = \pi_3 \cdot C_j \end{gathered} \tag{24}$$

where π represents the cost penalty factor, B_i represents the delivery time corresponding to task i, and T_{ij} represents the estimated completion time of task i on vehicle j. π_1 and π_2 represent the penalty factors for timely delivery and overdue delivery, respectively. On-time delivery can obtain positive rewards, while overdue delivery can be penalised. π_3 represents the satisfaction weight.

In order to cope with the changes in the dynamic traffic environment, the reward function is dynamically adjusted at each time step. If a traffic accident is detected, the penalty factor π_4 is introduced.

$$R_A = -\pi \cdot A_t - \pi_4 \cdot \pi_5 \tag{25}$$

where π_5 represents the severity of an accident in traffic conditions.

4.5 Construction of LSTM Model

In a dynamic traffic environment, the timeliness and accuracy of logistics scheduling are affected by many dynamic factors such as traffic flow fluctuations, sudden accidents and natural disasters. Some scholars have used attention-based spectral event graph neural networks for traffic flow prediction, but the model is too complex and inefficient [31].This study utilized the LSTM model [32–34] to extract dynamic information of traffic status in real time and optimize scheduling decisions. In LSTM, there are three gates in total: forget gate, input gate, and output gate. This is obtained with formula (26) [35]:

$$\begin{aligned} F1_s &= \sigma(T_{p[k1_{s-1}, z1_s]} + c_p) \\ i_s &= \sigma(T_{q[k1_{s-1}, z1_s]} + c_s) \\ F2_s &= \tanh(T_{x[k1_{s-1}, z1_s]} + c_x) \\ e1_s &= \sigma(T_{e[k1_{s-1}, z1_s]} + c_e) \\ n1_s &= e_s * \tanh(F_s) \end{aligned} \tag{26}$$

The prior hidden state is represented by $k1_{s-1}$, T_p represents the weight matrix, $z1_s$ represents the time input, the bias vector is represented by c_p, and $F2_s$ represents the vector of the new value of the unit state.

After completing the training of the LSTM model, the study combined it with the MAPPO algorithm and used the LSTM model to predict traffic state information as the state input in the MAPPO algorithm. The process is as follows:

(1) The LSTM model outputs the predicted traffic status for the next time period based on current and historical traffic flow, road conditions, and real-time events.

(2) In the Actor network of MAPPO, the traffic flow, speed, and other states predicted by LSTM are used as input, enabling each logistics vehicle agent to dynamically adjust route selection and scheduling decisions based on traffic conditions.

(3) The reward function of MAPPO considers transportation costs, time, and customer satisfaction, and makes real-time adjustments based on the dynamic traffic status predicted by LSTM. If the LSTM prediction shows

that some routes are severely congested, the system can impose penalties to encourage the agent to choose alternative routes.

5. INTELLIGENT LOGISTICS SCHEDULING EXPERIMENT UNDER DYNAMIC TRAFFIC ENVIRONMENT

5.1 Experimental Environment

Hardware environment: Intel Xeon Gold 6226R 2.9GHz, 16 cores, NVIDIA Tesla V100, 32GB, 128GB DDR4, 2TB SSD (Solid State Disk), operating system Windows 10.

Software environment: Python 3.8, PyTorch 1.10.0 framework, Matplotlib visualization tool, Stable-Baselines3 reinforcement learning library, OSM (Open Street Map) and Google maps API.

5.2 Experimental Data and Preprocessing

5.2.1 Experimental Data

The experimental data for this study were collected from real-time data from June to December 2023, including three aspects: data from the urban transportation system of Shenzhen Traffic Management Center, distribution data of a logistics company, and real-time data obtained from Google Maps API. The urban traffic system of Shenzhen Traffic Management Center includes dynamic traffic flow, vehicle speed, congestion index and accident conditions, and the corresponding data are timestamp, location, traffic flow, average speed, congestion level and accident identification, etc. The delivery data of logistics companies covers the departure point, destination, delivery time, delivery cost, fuel consumption and vehicle type, etc. The real-time data obtained by Google Maps API comprises traffic flow, average speed, and accident conditions. A total of 12,000 sets of traffic monitoring data were obtained, and a total of 52,136 sets of logistics company delivery data were collected. The experiment used a ten-fold cross-validation to divide the data set into a training set and a test set, 30% of which was used as a test set and 70% as a training set. The mean was taken as the final result. Some experimental data are shown in Table 1.

Table 1 shows the data of the urban traffic system of Shenzhen Traffic Management Center and the data of logistics company distribution after integration, including traffic flow, vehicle speed, congestion index, accident situation, logistics vehicle number, departure point, destination, delivery time, delivery cost, and fuel consumption.

5.2.2 Preprocessing

(1) Data cleaning

For data cleaning, data records with the greatest number of missing values were filtered out, and interpolation was used to supplement the missing traffic flow and speed data.

For abnormal data, the Z-score method was used to detect, screen out abnormal data points exceeding ± 3 times the standard deviation, and the quartile method was applied to detect extreme value data on fuel consumption and delivery time, and values below the first quartile or above the third quartile were treated by 1.5 times IQR (Interquartile Range) as abnormal.

(2) Data standardization

The study used the Min-Max normalization method for numerical variables such as traffic flow, vehicle speed, congestion index, delivery cost and fuel consumption to ensure that the values were normalized to the range of [0, 1]. The Min-Max normalization calculation formula is shown in formula (27).

$$H_n = \frac{H - H_{\min}}{H_{\max} - H_{\min}} \tag{27}$$

where H represents the original value and H_n represents the standardized value. $H_{\min}$ and $H_{\max}$ represent the minimum and maximum values of the variable, respectively.

(3) Data fusion

In order to fuse multi-source data such as traffic monitoring data, logistics company delivery data, and Google Maps API real-time data, this study aligned the spatiotemporal information of different data sets and matched the data of traffic conditions and delivery needs through association relationships.

First, the study converted the timestamps in the three data sources into UTC (Universal Time Coordinated) standard time. According to the timestamps, the traffic monitoring data and Google Maps API data with similar time and logistics distribution data were matched to ensure that they were in the same time window. For the starting and ending points in the logistics distribution data, and the geographic locations in the traffic monitoring data and Google Maps API real-time data, this paper used the geocoding function of the Geopy library to convert the addresses in the logistics data into longitude and latitude coordinates, and matched the records with geographic location errors less than 500 meters based on the nearest neighbor matching method [36–37].

After the timestamp and location alignment was completed, the study determined the starting point and end point locations. By establishing a mapping relationship between the traffic section ID and the delivery route section, the urban traffic system data and real-time traffic data were associated with each delivery record, and the final integrated traffic-logistics data table was output. Each record contained the departure point, end point and related information of the logistics delivery, the corresponding traffic flow, speed, congestion index and accident situation on the delivery route, etc., ensuring the multi-dimensional characteristics of the input data.

5.3 Experimental Design

This study has three objectives; optimize the delivery route, improve delivery efficiency, and reduce delivery time; improve customer satisfaction and reduce the impact of traffic congestion and accidents on the delivery process; optimize delivery costs and fuel consumption to achieve energy conservation and emission reduction.

Table 1 Partial experimental data.

Group	Traffic flow (vehicles/hour)	Vehicle speed (km/h)	Congestion index (0–10)	Accident (yes/no)	Logistics vehicle number	Departure point	Destination	Delivery time (minutes)	Delivery cost (yuan)	Fuel consumption (L)
1	1200	50	3	No	1	Area A warehouse	Point B in the city center	45	150	5
2	1800	35	7	No	1	A area warehouse	Supermarket in district C	60	180	6
3	2200	30	8	Yes	1	Area B warehouse	Residential area in district D	90	220	7
4	1600	45	4	No	2	Point B in the city center	Industrial park in the suburbs	70	200	6
5	2500	25	9	Yes	2	Area F cold storage	Point B in the city center	120	300	10
6	1400	55	2	No	2	Point B in the city center	Residential area in district D	35	120	4
7	1900	40	5	No	2	Suburban E industrial park	Point B in the city center	75	210	7
8	2100	28	7	Yes	3	A area warehouse	Supermarket in district C	95	250	9
9	1600	50	3	No	3	Point B in the city center	Cold storage in district F	40	140	5
10	1700	42	6	No	3	Area B warehouse	Point B in the city center	65	190	6

Table 2 Hyperparameters.

Parameters	Value	Parameters	Value
Learning rate	0.001	Number of hidden units	128
Discount factor	0.95	Number of layers	2
Batch size	64	Dropout rate	0.2
Update frequency	5	Sequence length	10

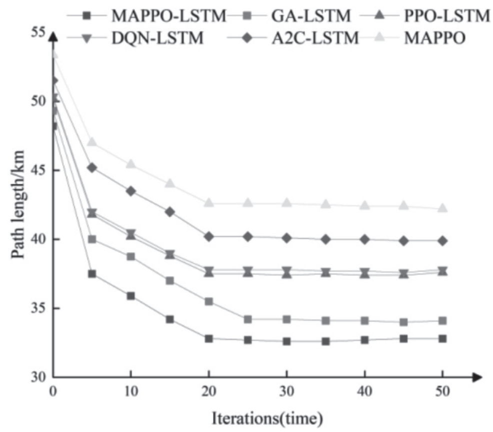

Figure 3 Iteration process of optimal paths of different algorithms.

Based on the above data, the experimental design steps used in this study are as follows:

(1) First, the missing value data is filled by interpolation, and the outlier data is detected and removed using the Z-score method and the quartile method. Then, the numerical data was standardized using the Min-Max standardization.

(2) After preliminary preprocessing, this study matched the traffic monitoring data and Google Maps API data of similar time with the logistics distribution data according to the timestamp, and combined the geocoding of the Geopy library to match the geographic location and the record according to the nearest matching method.

(3) A mapping relationship between traffic section ID and delivery route section was established, and urban traffic system data and real-time traffic data was associated with each delivery record.

(4) The study used the LSTM model to capture the dynamic information of the traffic environment, make short-term predictions of traffic conditions, and generate predicted traffic and congestion conditions.

(5) The study used the traffic flow, speed and other states predicted by LSTM as input to the MAPPO algorithm model, so that each logistics vehicle agent could dynamically adjust route selection and schedule decisions based on traffic conditions.

(6) This study used indicators such as delivery time, delivery cost, and fuel consumption to explore the situation of intelligent logistics dispatching logistics vehicles.

The hyperparameter settings are shown in Table 2.

From Table 2, it can be seen that for the MAPPO scheduling algorithm, the initial learning rate is set to 0.001, the discount factor is 0.95, the batch size is 64, and the update frequency is 5 steps. For the LSTM model, the number of hidden units is 128, the number of layers is 2, the dropout rate is 0.2, and the sequence length is 10.

5.4 Experimental Results

5.4.1 Iteration Process of the Optimal Path of Different Algorithms

This paper selected a delivery route as the object, and compared and analyzed the MAPPO-LSTM (Multi-Agent Proximal Policy Optimization-Long Short Term Memory) algorithm in the experiment with GA-LSTM (Genetic Algorithm-Long Short Term Memory), PPO-LSTM (Proximal Policy Optimization-Long Short Term Memory), DQN-LSTM (Deep Q-Network-Long Short Term Memory), A2C-LSTM (Advantage Actor Critic-Long Short Term Memory), and MAPPO algorithms. The process whereby the different algorithms find the optimal delivery path for logistics vehicles is evaluated. The iterative process of the optimal path of different algorithms is shown in Figure 3.

In Figure 3, the MAPPO-LSTM algorithm reached the optimal path after 35 iterations, with a path length of 32.6km, while the GA-LSTM, PPO-LSTM, and DQN-LSTM algorithms all reached the optimal path after 45 iterations, with path lengths of 34km, 37.4km, and 37.6km respectively. The A2C-LSTM algorithm and the MAPPO algorithm reached the optimal path after 50 iterations, with path lengths of 39.9km and 42.2km respectively.

Overall, the MAPPO-LSTM algorithm achieved the best results in terms of the number of iterations and the optimal path length, which is more in line with the actual needs of logistics vehicles.

(a)

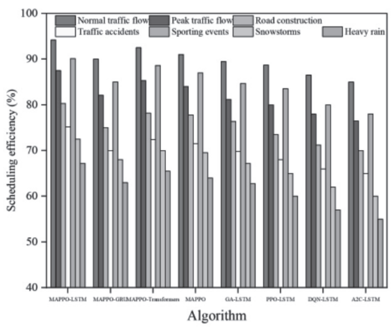

Figure 4(a)
Dispatch efficiency under different dynamic traffic conditions

(b)

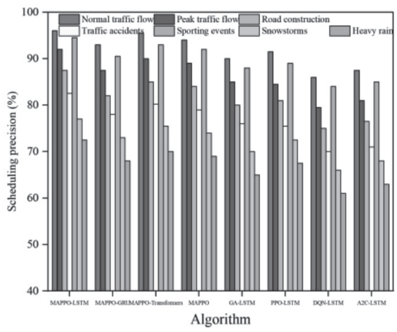

Figure 4(b)
Dispatch precision under different dynamic traffic conditions.

Figure 4 Dispatch efficiency and dispatch precision under different dynamic traffic conditions

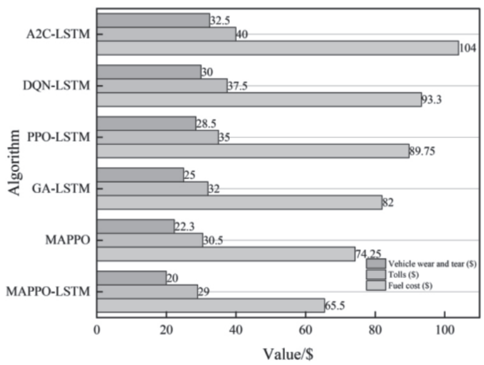

Figure 5 Transportation cost comparison results.

5.4.2 Scheduling Efficiency and Scheduling Precision under Different Dynamic Traffic Conditions

When logistics vehicles are transporting, they usually encounter various complex traffic conditions, and efficient scheduling becomes the key to timely delivery. The experiment measured the scheduling efficiency and scheduling precision of MAPPO-LSTM under different traffic conditions. The algorithms used for comparison were: MAPPO-GRU (Multi-Agent Proximal Policy Optimization-Gate Recurrent Unit), MAPPO-Transformers (Multi-Agent Proximal Policy Optimization-Transformers), MAPPO, GA-LSTM, PPO-LSTM, DQN-LSTM, A2C-LSTM.

The dispatching efficiency and dispatching precision of the algorithms under different dynamic traffic conditions are shown in Figure 4. In Figure 4, the dynamic traffic conditions include normal traffic flow, peak traffic flow, road construction, traffic accidents, sports events, snowstorms, heavy rains, etc.

In Figure 4 (a), for normal traffic flow, MAPPO-LSTM achieves the highest dispatch efficiency of 94.2%, which is 3.2% higher than the MAPPO algorithm. It can be seen that the introduction of the LSTM algorithm can effectively improve the ability to extract the dynamic traffic environment and ensure a higher dispatch efficiency, while the A2C-LSTM is lower, only 85%. In peak traffic flow, MAPPO-LSTM reached 87.5%, while DQN-LSTM and A2C-LSTM were 78% and 76.5% respectively. In traffic accidents, sports events, snowstorms, and rainstorms, MAPPO-LSTM's efficiency was 75.2%, 90.1%, 72.5%, and 67.2% respectively, significantly better than A2C-LSTM's 65%, 78%, 60%, and 55%, showing that MAPPO-LSTM is more robust in dealing with sudden and extreme conditions.

In Figure 4(b), MAPPO-LSTM has the best dispatch precision, reaching 96%, MAPPO-Transformers is 95.5%, and A2C-LSTM is only 87.5%. In the peak traffic flow scenario, MAPPO-LSTM has the highest precision, reaching 92%, while PPO-LSTM and GA-LSTM are 84.5% and 85%, respectively. In complex situations produced by factors such as road construction, traffic accidents and sports events, the precision of MAPPO-LSTM is 87.5%, 82.5% and 94.5% respectively. In the snowstorm and rainstorm scenarios, the precision of MAPPO-LSTM is 77% and 72.5% respectively, which is the best performance.

In summary, MAPPO-LSTM performed well in various traffic environments, and the dispatching efficiency and precision in extreme situations remained at a high level, demonstrating the sensitivity and adaptability of the LSTM structure to time series.

5.4.3 Transportation Cost Comparison

In order to further explore the intelligent scheduling performance of MAPPO-LSTM, the transportation costs for 10 deliveries are counted and the average is taken as the result. The transportation cost comparison results are shown in Figure 5 where the logistics cost is quantified using fuel cost, tolls and vehicle wear.

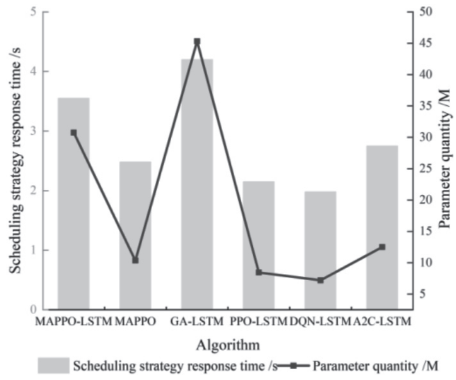

Figure 6 Comparison of scheduling strategy response time and parameter quantity.

Table 3 Sensitivity analysis results.

Weight of scheduling strategy	Scheduling efficiency (%)	Penalty factor	Scheduling efficiency (%)
0.1	78.65	0.05	85.32
0.3	82.43	0.1	88.17
0.5	87.21	0.15	94.20
0.7	89.36	0.2	70.82
0.9	94.20	0.25	65.14

In Figure 5, in terms of transportation cost, MAPPO-LSTM shows significant advantages in fuel cost, tolls and vehicle wear and tear. In terms of fuel cost, MAPPO-LSTM reaches 65.5$, which is significantly lower than 74.25$ of MAPPO algorithm and 104$ of A2C-LSTM algorithm. It can be seen that MAPPO-LSTM can optimize routes and reduce fuel consumption through intelligent scheduling. The fuel costs of GA-LSTM and PPO-LSTM are 82$ and 89.75$ respectively.

The toll incurred by applying MAPPO-LSTM was $29, which is lower than that of MAPPO and A2C-LSTM. This shows that MAPPO-LSTM is more intelligent in selecting road sections and time arrangements, avoiding more toll sections and reducing tolls. The tolls of DQN-LSTM and A2C-LSTM are 37.5$ and 40$ respectively.

The wear and tear cost incurred by applying MAPPO-LSTM is 20$, while the wear and tear cost of A2C-LSTM is the highest at 32.5$. Overall, MAPPO-LSTM has the lowest overall cost in terms of fuel cost, tolls and wear and tear, demonstrating its efficiency and economy in dynamic scheduling.

5.4.4 Scheduling Strategy Response Time and Complexity

Because the scheduling efficiency of the MAPPO-LSTM algorithm is good, the study can further verify the complexity of the algorithm and the scheduling strategy response time. The comparison results of the scheduling strategy response time and number of parameters are shown in Figure 6.

In Figure 6, in terms of scheduling strategy response time, the response time of MAPPO-LSTM reaches 3.55s, while the response times of PPO-LSTM and DQN-LSTM are 2.15s and 1.98s respectively. MAPPO-LSTM comprises a dual architecture, combining the parallelism of MAPPO and the timing processing capability of LSTM, resulting in an increase in response time. The response time of GA-LSTM is 4.2s (the highest level), indicating that the combination of GA and LSTM produces a high demand for computing resources during path optimization.

In terms of parameter quantity, MAPPO-LSTM reaches 30.75M. This is because it introduces additional parameters for temporal feature storage in the LSTM layer that improves the adaptability of the model in a dynamic environment. GA-LSTM has the highest number of parameters (45.32M). Overall, MAPPO-LSTM achieves good performance in terms of scheduling strategy response time and parameter quantity.

5.4.5 Sensitivity Analysis

In the training scheduling, the experiment increases the weight and penalty factor of the scheduling strategy in turn, determines the parameters that provide the best scheduling efficiency, and explores its sensitivity analysis. The results of the sensitivity analysis are shown in Table 3.

From Table 3, it can see that from the perspective of the impact of the weight of the dispatch strategy on the dispatch efficiency, the dispatch efficiency generally shows an upward trend as the weight increases. This shows that under lower weights, the contribution of strategy optimization to efficiency is limited, reaching a peak of 94.20% when the weight is 0.9. It can be seen that moderately increasing the weight can effectively enhance the adaptability of the dispatch strategy in different traffic conditions and make the system pay more attention to the optimization effect.

From the perspective of penalty factors, as the penalty factor increases from 0.05 to 0.15, the scheduling efficiency improves significantly, from 85.32% to 94.20%, indicating that a reasonable penalty factor can effectively avoid inefficient paths in the early stages. When it continues to increase to 0.2 and 0.25, the scheduling efficiency drops to

Table 4 Customer satisfaction analysis results.

Algorithm	Number of returned orders	Delivery time (h)	Repurchase rate (%)	Satisfaction score (15 points)
MAPPO-LSTM	5	2.35	82.45	14
MAPPO	8	2.75	78.12	13
GA-LSTM	7	2.6	76.45	13
PPO-LSTM	12	3.2	72.34	12
DQN-LSTM	10	3.1	70.85	12
A2C-LSTM	15	3.5	68.2	11

70.82% and 65.14%. Excessive penalties can easily cause the system to over-punish a few errors, resulting in a conservative overall scheduling strategy, which seriously affects scheduling efficiency.

5.4.6 Customer Satisfaction Analysis

Customer satisfaction plays a vital role in intelligent logistics scheduling, indicating whether the logistics system can effectively meet customers' requirements in terms of time, accuracy, flexibility and cost control needs. High customer satisfaction is directly related to customer retention and repurchase rates, and affects brand reputation and market competitiveness. In a dynamic traffic environment, the real-time adjustment and response efficiency of scheduling strategies are one of the key drivers of customer satisfaction. The experiment uses the number of returned orders and delivery time, repurchase rate and satisfaction score to comprehensively evaluate customer satisfaction. The results of customer satisfaction analysis are shown in Table 4. The customer satisfaction score was obtained via a questionnaire. A total of 3215 questionnaires were collected. The questionnaire contained the following three questions and participants responded on a Likert five-point scale, generating statistics for quantitative analysis.

Question 1: Are you satisfied with the on-time delivery of your order?

Question 2: When you contact customer service, does the response speed meet your expectations?

Question 3: Do you think the delivery fee is reasonable and consistent with the service quality?

In Table 4, it can be seen that the MAPPO-LSTM algorithm performs best, with the lowest number of returned orders being only 5, the shortest delivery time, only 2.35h, a repurchase rate of 82.45%, and the highest score of 14 points was achieved for customer satisfaction. The overall performance of the MAPPO and GA-LSTM algorithms is also relatively excellent, both reaching 13 points. The A2C-LSTM algorithm has the lowest satisfaction, with only 11 points. Results indicate that MAPPO-LSTM can effectively cope with dynamic traffic conditions, and can better ensure the timeliness and accuracy of delivery, reduce the return rate caused by delays, and improve the repurchase rate and overall customer satisfaction.

6. DISCUSSION

In this study, experimental results show that the MAPPO-LSTM algorithm is significantly superior to other comparison algorithms in terms of optimal path selection for logistics vehicles, dynamic traffic scheduling, transportation costs, response time, and customer satisfaction. MAPPO-LSTM achieves the optimal path with fewer iterations in path optimization, and exhibits high scheduling efficiency and accuracy in different traffic scenarios, especially in extreme traffic conditions, where its robustness is particularly evident. MAPPO-LSTM combines the parallelism of MAPPO and the time series processing capability of LSTM, and can adapt to complex dynamic environments more effectively. Moreover, it has the lowest costs in terms of fuel, tolls and wear, indicating the high efficiency of its route optimization.

This study provides a new direction for the optimization of logistics scheduling algorithms. The study introduces a combination of MAPPO and LSTM to achieve efficient and low-cost path optimization and scheduling decisions in complex dynamic traffic environments. MAPPO-LSTM improves the robustness of scheduling under extreme conditions, and also reaches a high level in time series feature extraction and parameter optimization, significantly improving the practical application of the scheduling system, and customer satisfaction. This study has potential for broader application, provides an effective reference for the design of intelligent transportation and dynamic scheduling systems, and establishes a technical foundation for the development of future intelligent logistics scheduling.

MAPPO-LSTM performed well in this study, but its dispatch response time and algorithm parameter count are relatively high, which increases the computing resource requirements for practical applications. This study did not investigate in depth the adaptability of the algorithm in a wider range of transportation networks and complex path environments. Future research could continue to optimize the structure of MAPPO-LSTM, reduce computational complexity, and improve response efficiency. At the same time, combined with the latest network security technology, it can enhance the data security of logistics dispatch in an open environment and respond to potential threats in complex network environments.

7. CONCLUSIONS

This study combines MAPPO and LSTM to study the intelligent logistics scheduling in a dynamic traffic environment and achieves good scheduling efficiency. The study uses the LSTM model to capture the dynamic characteristics of traffic flow and congestion, and incorporates the prediction results into the MAPPO algorithm to optimize the scheduling strategy of logistics vehicles. The experimental results show that the scheduling efficiency of the MAPPO-LSTM algorithm is significantly better than that of the traditional PPO algorithm, verifying its superiority in complex traffic environments. Although this study has made several contributions, it has several shortcomings. The method's adaptability in a wider traffic network and complex path environment is not fully considered, and the complexity is not well optimized. In future, this paper hopes to consider more external influencing factors to further improve the adaptability and reliability of the algorithm, and explore a more comprehensive intelligent scheduling solution to optimize the structure of MAPPO-LSTM and reduce computational complexity.

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