



Article

A Hybrid Optimization Approach for Multi-Criteria Decision Making in Emergency Response Coordination

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Abstract

Optimizing the allocation of emergency vehicles is essential for enhancing route-planning efficiency and ensuring road safety during traffic incidents. Traditional dispatch methods often struggle with complex scenarios due to their inability to integrate and balance multiple conflicting factors. This study proposes a multi-objective dispatch framework for emergency vehicles that integrates regression analysis, deep learning, and an enhanced ant colony algorithm. Key environmental factors (e.g., weather, visibility) are selected through logistic regression, and a BP neural network predicts the impact ranges of accidents. The adaptive ant colony algorithm optimizes dynamic routing through innovations such as adjusting state transition probability and implementing pheromone reward—penalty strategies. It achieves faster convergence (with a comprehensive index of 86 in 8 iterations compared to 158 in 20 iterations) and superior path quality (a 9% reduction in rescue time and a 12% decrease in costs). Compared with existing hybrid frameworks, this study is the first to integrate logistic regression-selected environmental factors with BP neural network-predicted accident impact ranges, and further proposes adaptive state transition and pheromone reward-penalty update mechanisms, thereby achieving faster convergence speed and superior path quality in dynamic multi-objective rescue route planning.

Keywords: component; emergency vehicle deployment; route optimization; regression analysis; multi-objective scheduling framework; dispatch efficiency

1. Introduction

The rapid expansion of highway networks and the increasing number of motor vehicles have resulted in more frequent traffic accidents, posing significant threats to both lives and property. As a result, ensuring traffic safety has become a key priority in transportation development and global research efforts. Research has shown that the severity of injuries in highway accidents is negatively correlated with the speed of emergency response [1]. Therefore, creating an effective system for scheduling emergency rescue operations is essential to minimize the impact of these accidents.

In emergency response scenarios, optimizing the dispatch and routing of rescue vehicles is crucial for enhancing response speed and making the most efficient use of available resources. By improving dispatch efficiency, these models contribute to reducing response times and increasing the effectiveness of rescue operations. As a result, a significant body of research, both domestically and internationally, has been dedicated to studying various



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emergency vehicle dispatch models. These models are typically categorized into two types: single-objective and multi-objective models, depending on the complexity and number of goals they aim to optimize. Single-objective models are designed to focus on one optimization criterion, such as minimizing vehicle travel time, reducing the time required to complete rescue tasks, or lowering overall operational costs. For example, Hao Z et al. [2] proposed a scheduling model for highway emergency rescue vehicles that accounts for delays caused by emergency lane occupation. Their model, based on the Location Routing Problem (LRP), optimizes the dispatch of rescue vehicles. In another study, Tan K et al. [3] focused on dispatching different types of rescue vehicles, including standard, oversized, and heavy-duty vehicles. They identified critical factors such as road section distance, grade, congestion, surface condition, and slope, which influence the overall road “weight.” By developing a path planning model that minimizes this road weight and incorporating vehicle constraints based on road conditions, they improved the efficiency of rescue operations [4]. These studies highlight the importance of optimizing emergency vehicle dispatch to improve response effectiveness and reduce casualty rates in traffic accidents. However, in real-world scenarios, emergency vehicle dispatch often involves multiple, conflicting objectives, limiting the applicability of single-objective models in practice.

In contrast, multi-objective dispatch models are more suited to the practical needs of emergency rescue operations as they take into account several optimization criteria simultaneously. These include reducing response times, increasing coverage, and minimizing costs. By balancing these competing objectives, such models deliver a more well-rounded and effective dispatch plan. For instance, research by Ferrer et al. [5] and Essus Y et al. [6] has introduced multi-objective models that enhance the efficiency of rescue operations while cutting down on operational expenses, providing valuable decision-making support for emergency management.

Vehicle dispatch models play a critical role in generating the necessary data for determining the most efficient rescue routes. The algorithms employed to solve these models are essential for effective path optimization. These solutions focus on identifying optimal routes and schedules for emergency vehicles, which is crucial for reducing response times and enhancing the success of rescue operations. The algorithms used to tackle vehicle dispatch models are generally divided into two main categories: exact algorithms and metaheuristic algorithms. Exact algorithms are based on constructing mathematical formulations for specific problems and solving them through rigorous mathematical techniques. For example, Schiffer M et al. [7] introduced the branch-and-price-and-cut approach to address the vehicle routing problem that includes time windows and manpower allocation constraints, aiming for the best possible solution. In a similar vein, Dayarian I et al. [8] proposed a multi-phase dynamic programming approach to tackle the problem of finding the least-cost path under stringent resource constraints. Lu Zhen et al. [4] proposed a two-stage stochastic programming model to optimize emergency vehicle deployment, employing a scenario generation method and validating it through experiments. However, the model’s computational complexity and reliance on commercial solvers limit its practical application. While these exact algorithms are effective for solving smaller-scale problems, they have limitations such as slow convergence rates and vulnerability to local optima when applied to larger and more complex scenarios [9].

The ant colony optimization (ACO) algorithm is highly valued for its robustness, parallel processing capabilities, and flexibility, making it a popular choice for tackling emergency vehicle routing problems. Liu J et al. [10] utilized ACO to address the issue of distributing emergency materials, integrating real-time road conditions to create more optimized routes for emergency vehicles. Despite its effectiveness, the standard ACO approach has certain limitations, such as excessive computational demands and slower

solution times. To overcome these drawbacks, a variety of improvements have been proposed by researchers both domestically and internationally to refine the algorithm's performance in path planning. For example, Yang B et al. [11] introduced an enhanced version of the double ant colony algorithm to overcome challenges like slow convergence, prolonged search durations, and the algorithm's tendency to get trapped in local optima. By altering the heuristic factor and integrating the max-min ant system for pheromone updating, their solution significantly boosts the algorithm's efficiency.

Despite these advancements, the multi-objective planning model faces two significant challenges. First, it often inadequately addresses complex environmental factors, which can limit its effectiveness in dynamic scenarios. Second, the ant colony algorithm is hindered by issues such as slow convergence and a tendency to become trapped in local optima, indicating areas where further improvement is needed. Therefore, this paper explores scheduling strategies and path optimization for emergency vehicle dispatch. This paper advances emergency vehicle dispatch research by integrating environmental factors like weather and congestion into the model using logistic regression and BP neural networks, enhancing prediction accuracy. It improves the ant colony optimization (ACO) algorithm with adaptive mechanisms and dynamic updates, addressing convergence and local optima issues. A multi-objective framework optimizes rescue time, cost, and delays while incorporating real-world constraints, and BP neural networks enable dynamic route adjustments based on real-time accident predictions, offering practical improvements for emergency response systems. Furthermore, in road transportation, accidents involving dangerous goods pose higher demands on the timeliness and professionalism of emergency response due to risks such as environmental pollution, explosions, and toxicity. Delayed responses to such incidents may not only lead to severe casualties and property damage but also trigger major public safety and environmental crises. Therefore, incorporating dangerous goods transportation accidents into the emergency vehicle dispatch model is crucial for enhancing the robustness and adaptability of the rescue system. Future research could further integrate theories related to "dangerous goods transport in urban areas" and "sustainable emergency traffic management" to extend the model's applicability to diverse accident scenarios [12].

The proposed method is validated with a case study on the highway network and surrounding roads in China, demonstrating its feasibility and effectiveness. By focusing on these enhancements, the study aims to provide a more efficient and reliable solution for emergency vehicle dispatch, ultimately improving rescue operations and reducing response times in critical situations.

The contributions of this paper are threefold:

1. A logistic regression-based environmental factor screening mechanism is proposed to dynamically identify the most influential environmental variables on accidents;
2. A BP neural network-based accident impact prediction module is constructed to enable real-time estimation of accident-affected road lengths;
3. Adaptive state transition rules and pheromone reward-penalty strategies are designed, significantly improving the convergence speed and global search capability of ACO in rescue route planning.

These enhancements enable the proposed framework to exhibit better adaptability and optimization performance in dynamic multi-objective rescue dispatch.

2. Optimization Framework

The problem of highway emergency vehicle dispatch involves multiple aspects, such as vehicle scheduling and rescue route planning. In actual emergency rescue operations, managers must determine the dispatch of emergency vehicles and formulate optimized

dispatch plans in complex environments. Based on the improved ant colony algorithm, this study addresses two main issues: analyzing the impact of complex environments on highway traffic accidents and establishing an intelligent dispatch model for highway emergency vehicles. The detailed research content is elaborated below.

2.1. Complex Environmental Factors Extraction

Adverse weather conditions such as snow, fog, and rain significantly contribute to highway accidents, often resulting in severe losses and wide impact areas, thereby complicating rescue efforts [13]. Accurately understanding the effects of these complex environments on accidents and predicting rescue times are crucial for effective emergency dispatch. This study employs logistic regression and BP neural network analysis to evaluate the impact of complex environments on the length of accident-affected road sections, providing critical support for optimizing rescue operations.

Logistic regression is an important model for categorical data modeling, widely used in transportation [14], medicine [15], and social sciences [16]. A binary logistic regression model is suitable for this study, where environmental indicator data are the independent variables, and whether the accident-affected road length exceeds 1 km (0 for less than 1 km, 1 for more than 1 km) is the dependent variable. Using the probability of the highway accident affecting a segment length exceeding 1 km as the dependent variable and various environmental factors $x_1, x_2, \dots, x_i, x_1, x_2, \dots, x_i$ as the independent variables, a Logistic regression equation can be established to obtain the probability of the highway accident affecting a segment length exceeding 1 km, as shown in Equation (1):

$$P = \frac{\exp\left(b_0 + \sum_{k=1}^k b_k x_k\right)}{1 + \exp\left(b_0 + \sum_{k=1}^k b_k x_k\right)} \quad (1)$$

where P represents the likelihood that the length of the affected highway segment exceeds 1 km after an accident in a complex environment, quantified as a number calculated by the formula. The larger the value, the more likely it is that the affected segment length will exceed 1 km after the accident; conversely, the smaller the value, the less likely it is to occur.

In this study, SPSS 30 data analysis software is utilized to conduct a Logistic regression analysis. The Logistic regression analysis tool within the SPSS module is employed, using stepwise regression for the analysis. First, all environmental impact factor variables are input into the Logistic regression analysis tool for model fitting. This process outputs the correlation degree of each environmental variable with the dependent variable. Environmental factors with a high correlation to the dependent variable are retained, while those with a low correlation are eliminated. Next, the retained environmental factors are input into the SPSS correlation test module to remove highly autocorrelated environmental factors. Finally, the remaining environmental variables, which are not correlated and have low autocorrelation, are fitted into a linear model.

Data Sources and Preprocessing

The data used in this study are sourced from the Shandong Provincial Expressway Management Center, covering traffic accident records and environmental monitoring data from 2019 to 2023, comprising a total of 2347 accident cases. Data fields include accident time, location, weather conditions (temperature, humidity, visibility, wind speed, etc.), road type, traffic flow, etc. All data underwent missing value imputation, outlier removal, and standardization. The dataset is publicly available at [repository link] for verification and reproduction by future research.

2.2. Forecasting the Extent of Accident Effects

BP neural network prediction is implemented using Matlab. The input environmental variables obtained from the logistic regression model include temperature, humidity, pressure, visibility, wind speed, and day/night. A BP neural network, typically structured with three layers (input, hidden, and output), is used for prediction. The number of nodes in the hidden layer is determined empirically by the formula $h' = m' + n' + a'$, where m' is the number of input nodes, n' is the number of output nodes, and a' is an adjustment constant between 1 and 10. The calculation process involves the input layer to hidden layer and hidden layer to output layer computations. The structure of the BP neural network is illustrated in Figure 1.

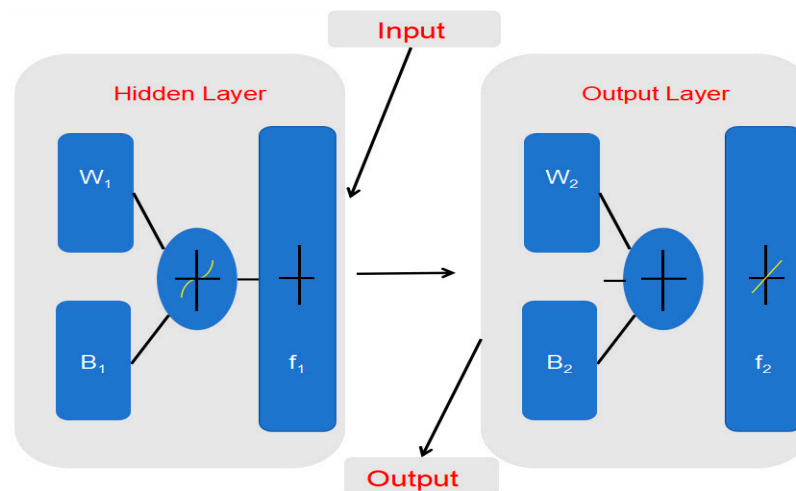


Figure 1. BP neural network.

A single-hidden-layer BP network structure was selected, with the number of hidden nodes determined through trial and error. Performance comparisons were conducted on the same data with different numbers of hidden layers and nodes. Experiments show that a hidden layer with 6 nodes achieves the best balance between prediction accuracy and training efficiency. Additionally, LSTM and GRU networks were tested, but the BP network demonstrated more stable performance and faster training speed in this task.

The computation of the input layer to the hidden layer is the first key step in a neural network that maps the input data onto the neurons in the hidden layer. In this process, each hidden layer neuron will receive the signal from the input layer and sum the weights, and then process the activation function to obtain the output of the hidden layer. For each neuron j of the hidden layer, the input z_j^1 is calculated as shown in Equation (2):

$$z_j^1 = \sum_{i=1}^l W_{ji}^1 x_i + B_{j0}^1 \quad (2)$$

Then, the input z_j^1 is processed through the activation function g to obtain the output a_j^1 of the hidden layer, as shown in Equation (3):

$$a_j^1 = g(z_j^1) \quad (3)$$

The hidden-to-output layer calculation is the second key step in the neural network that maps the output of the hidden layer onto the neurons in the output layer. In this process, each output layer neuron will receive the signal from the hidden layer, and sum the weights by weight, and then process the activation function to obtain the output of the

output layer. Specifically, for the neurons in each output layer, its input z_s^2 is calculated as shown in Equation (4):

$$z_s^2 = \sum_{j=1}^j W_{sj}^2 a_j + B_{s0}^2 \quad (4)$$

W_{sj}^2 is the weight connecting the hidden layer node j and the output layer node s , and B_{s0}^2 is the bias of the output layer neurons. Then the z_s^2 is processed through the activation function to obtain the output h_W of the output layer, as shown in Equation (5):

$$h_W = g(z_s^2) \quad (5)$$

The mean square error (mean square error, MSE) is selected as an index to evaluate and compare the model prediction performance. Select the correlation coefficient to measure the strength and direction of the linear relationship between the two variables. The correlation definition is shown in Equation (6):

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (6)$$

$$R = \frac{\sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y}_i)}{\sqrt{\sum_{i=1}^N (x_i - \bar{x})^2 \sum_{i=1}^N (y_i - \bar{y}_i)^2}} \quad (7)$$

where y_i is the true value; $\hat{y}_i$ is the prediction result; and N is the number of predicted samples. The update parameters of the gradient descent are shown in Equation (8):

$$W_{ij}^l = W_{ij}^l - \alpha \frac{\partial MSE}{\partial W_{ij}^l} \quad (8)$$

where α is the learning rate, and l is the hierarchical index.

This study uses the MATLAB R2025a programming software to implement the BP neural network prediction. First, the logistic regression model can obtain environmental variables related to the length of highway traffic accidents, and take the relevant environmental variables as the input to the BP neural network. Therefore, the input environmental variables in this study include temperature, humidity, pressure, visibility, wind speed, and day and night. Second, the article contains a hidden layer, through which the data is passed to the hidden layer through the input layer. Each neuron in the hidden layer will be weighted to sum the input data and obtain the activation value through the activation function Sigmoid function, as the output of that neuron. This output is passed to the output layer for further classification. During back propagation, the output of the output layer is compared with the actual value to calculate the error. This process iterates repeatedly until the error is small enough. Through this process, the hidden layer gradually learns how to map the input data to higher-dimensional representations, so that the output layer can accurately classify different types of road lengths. Finally, the neural network will be able to output the corresponding classification results according to the input data. The output layer outputs two neurons, representing two types: neurons with a road length of between 0 and 1 km and neurons with a length of more than 1 km. During the experiment, the BP neural network has a hidden layer of 6 neurons, experimental training times of 1000, training iterations of 1000, learning rate 0.01, and training accuracy 1×10^{-6} .

During the training of the BP neural network, we conducted six performance evaluations within the 133rd training cycle, with the optimal performance observed at the 127th training cycle. The values of the loss function and momentum parameters of the current

model were optimal. In the current training period, the mean squared error of the training, validation and test sets is infinitely close to 0.06067.

2.3. Design of the System Framework

To simplify the problem, several assumptions are made. First, it is assumed that the emergency rescue center has sufficient vehicle resources to ensure rapid response when needed. Second, the speed of emergency vehicles during tasks is set to the average speed of the road section for calculation and evaluation of dispatch efficiency. Upon arriving at the accident site, immediate rescue and treatment are assumed, with the journey to the next emergency handling point still applicable to the path optimization model constructed in this study. Additionally, no delays are assumed before the departure of emergency vehicles, and extra time consumption, such as refueling and unloading, is not considered during rescue operations.

Further assumptions include each emergency vehicle focusing on a single traffic accident to enhance resource utilization efficiency and site response speed. Emergency vehicles are assumed to travel on the emergency lane of highways without considering lane occupancy issues, ensuring priority passage to reach the accident site in the shortest time. Finally, emergency vehicles are assumed to have certain priority passage rights to quickly and safely navigate congested or busy sections, improving the efficiency and effectiveness of emergency response.

The overall objective function in this paper aims to minimize three key factors: rescue time φ_1 , rescue cost φ_2 , and delay penalties φ_3 . Rescue time encompasses both travel time and delay time, while emergency rescue costs include fixed costs, fuel consumption costs, and capacity costs. Additionally, delay penalties are considered part of the emergency rescue operation. These relationships are expressed in Equation (9):

$$\begin{aligned} \min z &= \omega_1 \varphi_1 + \omega_2 \varphi_2 + \omega_3 \varphi_3 \\ \omega_1 + \omega_2 + \omega_3 &= 1 \quad \omega_1, \omega_2, \omega_3 \in [0, 1] \end{aligned} \quad (9)$$

The weights ω_1 , ω_2 , and ω_3 represent the importance of rescue time, cost, and delay penalty, respectively, and are determined based on expert questionnaires and the Analytic Hierarchy Process (AHP) [17]. To further analyze the impact of weight variations on dispatch outcomes, a sensitivity analysis was conducted. The analysis shows that the dispatch scheme remains stable within the range $\omega_1 \in [0.4, 0.6]$, aligning with the practical need to balance time and cost in emergency rescue.

The travel time estimation for road segments uses the Bureau of Public Roads (BPR) model [18], as shown in Equation (10):

$$t_{ij} = \frac{L_{ij}}{v_{ij}} \left[1 + \alpha \left(\frac{Q_{ij}}{C_{ij}} \right)^\beta \right] \quad (10)$$

where t_{ij} is the rescue time from the rescue point i to the accident point j , Q_{ij} is the actual traffic flow, L_{ij} is the road length, v_{ij} is the design speed, C_{ij} is the traffic capacity, and α and β are coefficients reflecting the degree of congestion.

However, the classical BPR model often falls short in practical scenarios. The travel time for emergency rescue vehicles is significantly influenced by complex environments and the current traffic accident, which can lead to severe traffic congestion. The traditional BPR function (Equation (10)) estimates travel time for general vehicles on road segments. To reflect the fact that emergency vehicles can use reserved lanes or have priority passage rights, this study introduces an emergency lane adjustment coefficient λ_{ij} (typically $\lambda_{ij} \in [0.8, 1.0]$), dynamically adjusted based on the availability of emergency lanes and

real-time traffic control) to modify the free-flow speed v_{ij} . Furthermore, the congestion time around the accident site t'_{ij} , caused by the accident itself, is dynamically calculated based on the “accident-affected road length” predicted by the BP neural network in Section 2.2, and is activated by the 0–1 variable ψ in Equation (11). This modeling approach better aligns with the actual travel behavior of emergency vehicles in real-world road networks. Therefore, it is crucial to account for congestion time when calculating the travel time of emergency vehicles. The definition of congestion time is derived from the predicted length of the accident-affected road segment in complex environments, as discussed earlier. Specifically, when the affected segment length exceeds 1 km, the corresponding emergency response time should be increased. Taking traffic congestion into account, the revised definition of emergency rescue travel time is provided in Equation (11).

$$t_{ij} = \frac{L_{ij}}{v_{ij}} \left[1 + \alpha \left(\frac{Q_{ij}}{C_{ij}} \right)^\beta \right] + \psi t'_{ij} \quad (11)$$

where Equation (12) defines the accident impact range length as a 0–1 variable:

$$\psi = \begin{cases} 1 \\ 0 \end{cases} \quad (12)$$

When the length of the affected segment exceeds 1 km, $\psi = 1$; otherwise, $\psi = 0$. The term t'_{ij} represents the congestion time for emergency rescue vehicles, defined based on the impact length of the traffic accident.

While the emergency response process emphasizes a “people-oriented” approach, which reflects a more cost-effective strategy, ensuring the economic efficiency of emergency response is crucial, especially in traffic accidents that do not involve life-threatening situations. Therefore, the second objective function of this study is to minimize the scheduling cost of emergency rescue, denoted as φ_2 , as shown in Equation (13). This cost primarily includes fixed costs fix^f and transportation costs trp^f .

$$\varphi_2 = \sum_{i \in I} \sum_{j \in J} \sum_{f \in F} C_{ij}^f x_{ij}^f + \sum_{i \in I} \sum_{h' \in H'} \sum_{v \in V} \sum_{f \in F} P_v C_{ih'}^f y_{ih'}^f \quad (13)$$

$$C_{ij}^f = \sum_{i \in I} \sum_{j \in J} \sum_{f \in F} fix_{ij}^f + trp_{ij}^f \quad (14)$$

$$fix_{ij}^f = \sum_{i \in I} \sum_{j \in J} \sum_{f \in F} x_{ij}^f c_f \quad (15)$$

$$trp_{ij}^f = \sum_{i \in I} \sum_{j \in J} \sum_{f \in F} d_{ij}^f \times \uparrow \Gamma \quad (16)$$

Equation (13) represents the objective of minimizing both the costs of current and potential accidents, where C_{ij}^f denotes the total cost for emergency rescue points. Equation (14) details that the rescue cost comprises both fixed and transportation costs. Equation (15) specifies that the total fixed cost per vehicle is calculated as the number of dispatched vehicles multiplied by the unit cost per vehicle. Equation 16 indicates that the transportation cost per vehicle is equivalent to the fuel cost.

The rescue cost φ_2 defined in Equations (13)–(16) primarily covers fixed and transportation costs during dispatch. To enhance the long-term preparedness and response capability of the emergency system, it is advisable to incorporate training and exercise costs

into the model, aligning with the emergency management principle of “prevention first, exercise second.” This component can be expressed as (17) [19].

$$\varphi_{2, \text{training}} = \sum_{f \in F} \gamma_f \cdot n_f \quad (17)$$

The delay penalty function is the third sub-objective of this study, aimed at reducing the latest possible time for emergency vehicles to arrive at the incident scene, thereby reflecting the efficiency of emergency service levels [20]. Due to the specific nature of highway emergency rescue, the penalty for delays stabilizes after reaching a certain time threshold, rather than continuously increasing. Therefore, this study employs a mixed model of unilateral hard and soft time windows. If a vehicle arrives before ET, there is no delay penalty. If it arrives within the time window [ET, LET], a unilateral soft time window penalty is applied. If the arrival time exceeds the latest allowed time, LET, a unilateral hard time window penalty is applied. Constraints for the unilateral mixed time windows for emergency vehicles are illustrated in Figure 2, with all delays in reaching the accident and potential accident points penalized as shown in Equation (18).

$$\varphi_3 = \begin{cases} 0, & t_{ij} < ET \\ \sum_{i \in I} \sum_{j \in J} p' \times \frac{t_{ij} - ET}{LET - ET}, & t_{ij} \in [ET, LET] \\ p', & t_{ij} > ET \end{cases} \quad (18)$$

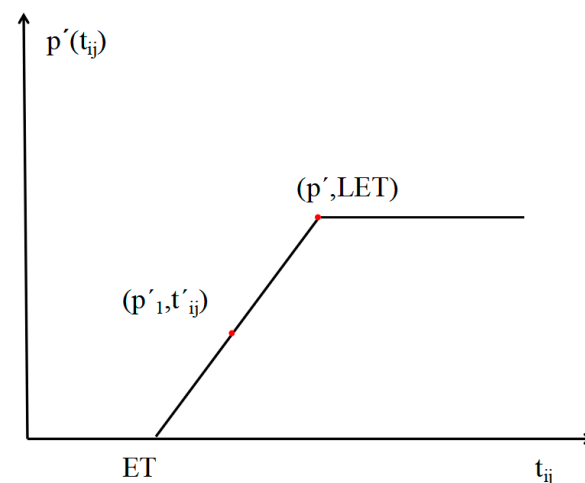


Figure 2. Unilateral hybrid time window penalty function.

3. Solving Method Based on Improved Ant Colony Algorithm

3.1. Enhanced ACO Algorithm

In traditional ACO algorithms, ants follow state transition rules to determine the next path point. The core idea of this rule is to first identify and calculate the transition probabilities of all possible next path points. Then, using a roulette wheel selection mechanism, one of these candidates is randomly chosen as the next path point. According to Equation (19), the probability of selecting a feasible point is higher when the weighted product of pheromone and heuristic information $[\tau'_{ij}(t)]^{\alpha'} \cdot [\eta'_{ij}(t)]^{\beta'}$ is larger. Although the roulette wheel mechanism performs well in maintaining path diversity, its tendency to select the current optimal feasible point is low due to the insignificant differences in the weighted products of pheromone and heuristic information among feasible points, which

affects the convergence speed of the algorithm. Therefore, an improvement to the state transition probability is proposed as shown in Equation (19):

$$p_j' = \begin{cases} \operatorname{argmax}_{s' \in \text{allowed}_k} \left\{ [\tau_{ij}'(t)]^{\alpha'} [\eta_{ij}'(t)]^{\beta'} \right\}, & q < q_0 \\ J', & q > q_0 \end{cases} \quad (19)$$

where p_j' represents the next path point, J' is the next path point selected according to Equation (18) with probability q_0 , and q_0 is a dynamic selection factor within (0, 1) to adaptively update the selection ratio, thereby adjusting the algorithm's exploration of new paths. Equation (20) gives the formula for q_0 .

$$q_0 = \frac{1}{1 + e^{3 \text{Iter}_{\text{num}}}} \quad (20)$$

After improvement, q_0 decreases with the increase in the number of iterations. In the early stages of the algorithm, a larger q_0 allows the algorithm a greater chance of selecting points with the highest pheromone and heuristic information weighted product, speeding up convergence. This enhances the search efficiency in the initial phase of the algorithm. In the later stages, a smaller q_0 increases the probability of ants selecting nodes based on roulette wheel selection, ensuring the global search capability of the algorithm.

3.2. Enhanced Pheromone Update Strategies

The pheromone update strategy in this paper is improved mainly from three aspects: the pheromone reward and penalty principles, pheromone concentration limits, and the improved pheromone evaporation factor.

3.2.1. Pheromone Reward and Penalty Principles

After each iteration, the ant colony algorithm updates the pheromones on the paths based on global guiding rules to enhance the search efficiency for optimal solutions. However, the global pheromone update in traditional ant colony algorithms exhibits a certain lag, which may not timely guide ants to the optimal solution. To address this issue, this paper employs the AC pheromone update model and proposes a high-quality ant update rule. This rule adds rewards to the optimal traversal paths based on model evaluation metrics, increasing the pheromone on these paths to enhance the probability that subsequent ants will choose these paths. Conversely, it imposes penalties on paths with poor performance, reducing the pheromone on these paths and decreasing the probability of subsequent ants selecting them. The improved pheromone update strategy is shown in the following equations, with Equation (21) introducing a reward factor to enhance the pheromone of optimal paths and Equation (22) weakening the pheromone of the worst ants' paths.

$$\tau_{ij}'(t) = \begin{cases} \tau_{ij}'(t), & \tau_{ij}'(t) \geq \tau_{\max}' \\ \tau_{ij}'(t), & \tau_{\min}' < \tau_{ij}'(t) < \tau_{\max}' \\ \tau_{ij}'(t), & \tau_{ij}'(t) \leq \tau_{\min}' \end{cases} \quad (21)$$

$$\tau_{ij}'(t+1) = (1 - \rho') \tau_{ij}'(t) + \rho' \left(-\frac{Q'}{Z_{\text{worst}}} \right) + \rho' \left(-\frac{Q'}{Z_{\text{worst}}} \right), ij \in p_{\text{worst}} \quad (22)$$

By incorporating the reward and penalty mechanism, the updated strategy can largely prevent subsequent ants from getting stuck at path edges due to taboo list restrictions, increasing the number of effective solutions generated in each iteration and improving the likelihood of finding the global optimal solution.

3.2.2. Pheromone Concentration Limits

To avoid issues such as algorithm failure or slow convergence due to excessively high or low pheromone concentrations, Equation (23) sets limits on pheromone concentration. Limiting the upper bound of pheromone concentration prevents it from growing indefinitely, which could cause the algorithm to prematurely converge to a local optimum and fail to explore a broader solution space [21]. At the same time, setting a lower bound prevents the pheromone concentration from becoming too small, ensuring the algorithm's exploratory capability and avoiding getting trapped in local optima.

$$\tau'_{ij}(t) = \begin{cases} \tau'_{max}, & \tau'_{ij}(t) \geq \tau'_{max} \\ \tau'_{ij}(t), & \tau'_{min} < \tau'_{ij}(t) < \tau'_{max} \\ \tau'_{min}, & \tau'_{ij}(t) \leq \tau'_{min} \end{cases} \quad (23)$$

3.2.3. Improved Pheromone Evaporation Factor

In the process of searching for the optimal solution using ant colony algorithms, the pheromone concentration update primarily simulates the natural accumulation and evaporation of pheromones over time. Besides the pheromone concentration update rules, the pheromone evaporation factor also impacts the algorithm's performance. In basic ant colony algorithms, the pheromone evaporation coefficient ρ' is a fixed constant, which is not favorable for maintaining the global search capability in the early stages and the rapid convergence capability in the later stages of the algorithm. Therefore, this paper adopts a dynamic pheromone evaporation factor ρ' to adjust the algorithm's globality and convergence speed, ensuring path diversity while improving convergence speed [22]. The dynamic factor is shown in Equation (24).

$$\rho'(t+1) = \begin{cases} \frac{Iter_{max} - Iter_{min}}{Z_{best}} \times \frac{1}{e^{1.1 - \rho'(t)}}, & \rho' \geq \rho'_{min} \\ \rho'_{min}, & \text{otherwise} \end{cases} \quad (24)$$

In the early stages of the algorithm, because the optimal comprehensive performance indicator Z_{best} is large, the pheromone evaporation factor ρ' is relatively small, leading to minimal differences in pheromone concentrations across paths, which enhances the ants' global search range. As the ant colony algorithm iterates, Z_{best} decreases, causing ρ' to increase rapidly, which in turn increases the pheromone concentration on each path, enhancing the guidance function of the ant colony algorithm and accelerating convergence.

4. Practical Application Example

4.1. Refined State Transition Guidelines

This paper uses part of the expressway network and surrounding urban road network in Dongying City, Shandong Province, as the research area. The intelligent scheduling model for emergency vehicles on expressways in complex environments is validated using the dispatching of ambulances, police cars, and road patrol vehicles as an example. The intelligent dispatching experiment of rescue vehicles mainly includes two scenarios: one-to-one scenario where one rescue point serves one accident point, and multi-to-one scenario, where multiple rescue points serve a single accident point. The evaluation metrics chosen for this study include time, cost, and delay penalties. However, in actual rescue operations, emergency rescue points are often located near highways, and delays often occur before the penalty threshold is reached. Therefore, the average speed of emergency vehicles is crucial for rescue operations; thus, the evaluation metrics for the model are set as rescue time, cost, and average speed.

In the one-to-one rescue scenario, where one rescue point services one accident point, the focus is solely on the path planning of emergency rescue vehicles without involving vehicle selection and scheduling. In this scenario, assume a traffic accident occurs at the red dot (Node 13), and there is only one rescue point at the red star (Node 90) to handle the rescue, as shown in Figure 3.

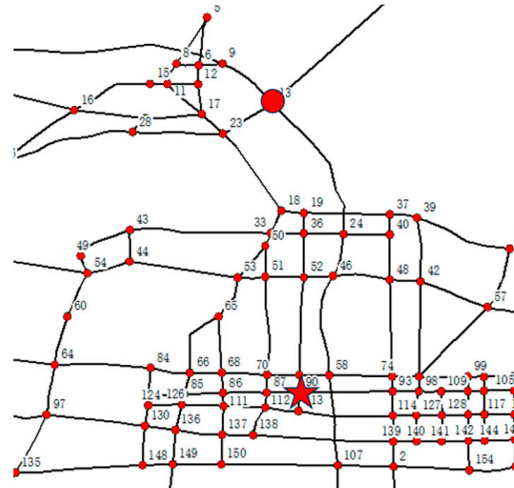


Figure 3. Distribution of One-to-One Rescue Points and Accident Points.

To verify the effectiveness of the improved ant colony algorithm, both the traditional and improved ant colony algorithms are used to plan paths from the rescue point to the accident point, and their performance metrics are compared. Figure 4a shows the path obtained using the traditional ant colony algorithm, while Figure 4b shows the path obtained using the improved ant colony algorithm. The red paths represent the vehicle routes. Table 1 and Figure 4 present the comparative data and charts for the performance metrics of different ant colony algorithms. As shown in Figure 4a, the traditional ant colony algorithm chose the path nodes 90-72-52-36-19-18-23-13, which involves traveling from surrounding roads to the highway accident point. In contrast, as shown in Figure 4b, the improved ant colony algorithm chose the path nodes 90-72-52-46-24-13. Converting these nodes to actual roads in Dongying City, the route is: starting from Bei yi Road, traveling north along Lushan Road for 7.5 km to reach Tongxing Road, then east along Tongxing Road for 1.2 km to reach Kenli Interchange and enter G18 Rongwu Expressway, continuing north on Rongwu Expressway for 21.6 km to reach the accident site at the Port Surcharge Hub. It is evident that the improved ant colony algorithm selected a route with a much higher proportion of highway usage compared to the traditional ant colony algorithm, which aligns better with practical highway rescue path planning.

Based on Table 1 and Figure 5, the improved ant colony algorithm shows significantly better metrics in rescue time, cost, and average speed compared to the basic ant colony algorithm, indicating that the improved algorithm performs better. The improved ant colony algorithm yields better comprehensive performance in rescue path planning, demonstrating its effectiveness.

Table 1. Comparison of Path Results Between Traditional and Improved Ant Colony Algorithms.

The Type of Algorithm	Path	Rescue Time (min)
Traditional ant colony algorithms	90-72-52-36-19-18-23-13	24.39
Improving the ant colony algorithm	90-72-52-46-24-13	22.25

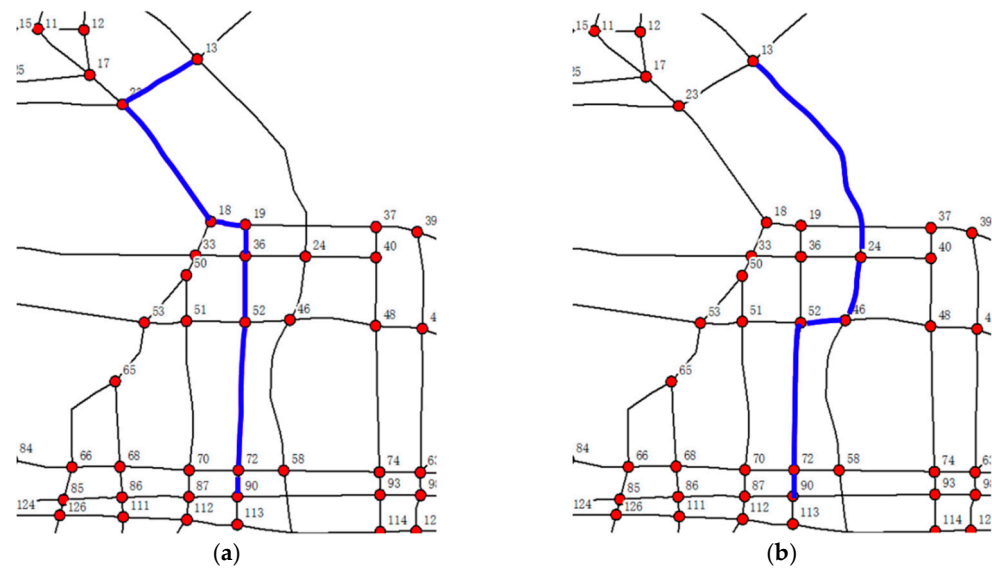


Figure 4. (a) Paths Obtained by Traditional; (b) Improved Ant Colony Algorithms.

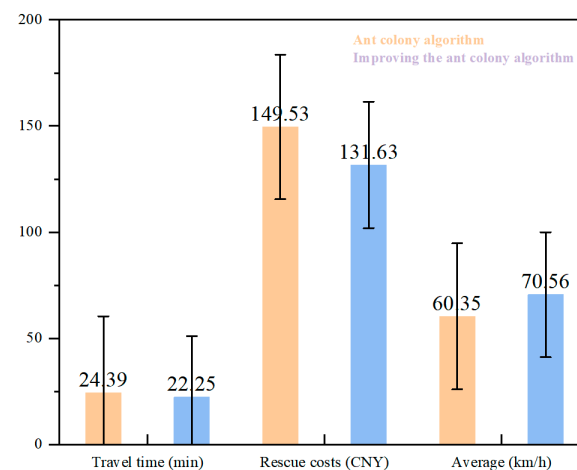


Figure 5. Comparison of Metrics.

Figure 6 illustrates the convergence of the objective function for both traditional and improved ant colony algorithms. The red line represents the convergence process of the traditional ant colony algorithm, while the blue line represents the improved ant colony algorithm. It is clear from Figure 6 that the traditional ant colony algorithm converges to a minimum comprehensive performance of 158 only after 20 iterations, whereas the improved algorithm converges to a minimum comprehensive performance of 86 after just 8 iterations. This clearly indicates that the improved ant colony algorithm has significantly better convergence speed and overall performance compared to the traditional algorithm, validating its effectiveness and reasonableness in this model scenario.

4.2. Model Application

In the multi-to-one emergency vehicle scheduling scenario, a decision needs to be made to determine emergency rescue points around the accident site, and then the proposed intelligent scheduling model is used to minimize the objective function to determine which rescue point should dispatch emergency vehicles. In this scenario, assume a traffic accident occurs at the red dot (topological node 46) on Dongqing Expressway, with three nearby rescue points available: nodes 17, 136, and 154, as shown in Figure 7. The intelligent scheduling scheme is determined using the improved ant colony algorithm.

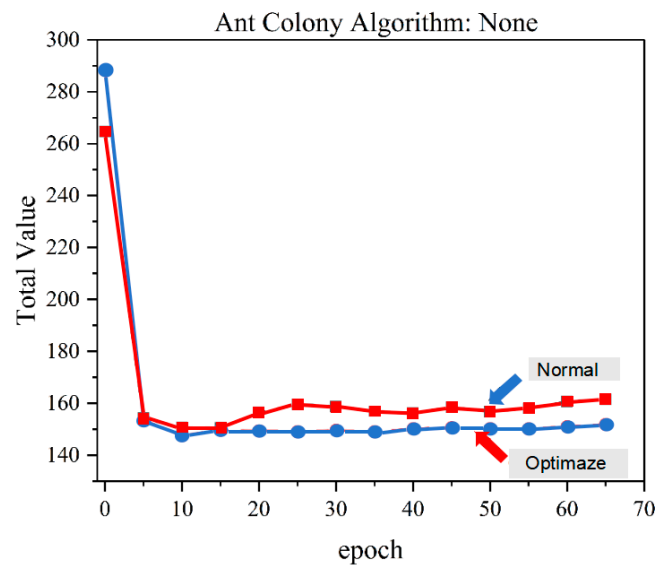


Figure 6. Convergence Comparison Before and After Improvement.

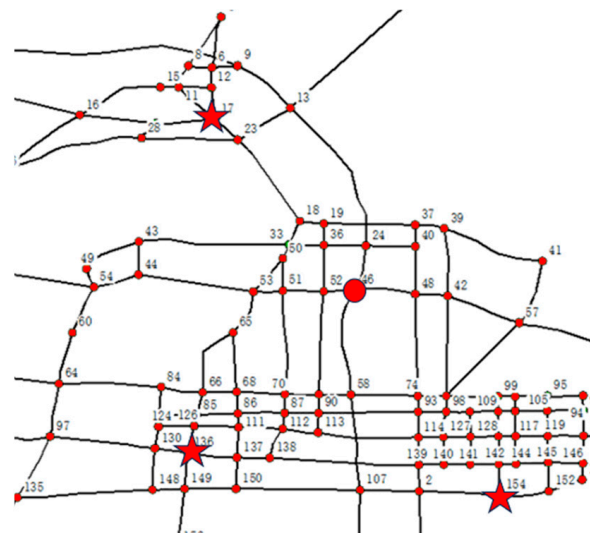


Figure 7. Distribution of Multi-to-One Rescue Points and Accident Points.

Running the improved ant colony algorithm for each of the three rescue points, the dispatch paths are shown in Figure 8. Assume the light blue path is for vehicle 1, the orange path is for vehicle 2, and the dark blue path is for vehicle 3. The paths are: Vehicle 1: 17-23-18-19-36-52-46; Vehicle2: 154-2-139-114-93-74-48-46; Vehicle3: 136-126-85-66-65-53-51-52-46. Performance metrics are shown in Table 2 and Figure 9.

Table 2. Path Metrics Using Improved Ant Colony Algorithm.

Vehicle Number	Travel Time (min)	Rescue Costs (CNY)	Average (km/h)
1	17.74	121.75	60.16
2	23.52	128.66	60.23
3	19.46	123.21	60.54
1	17.74	121.75	60.16

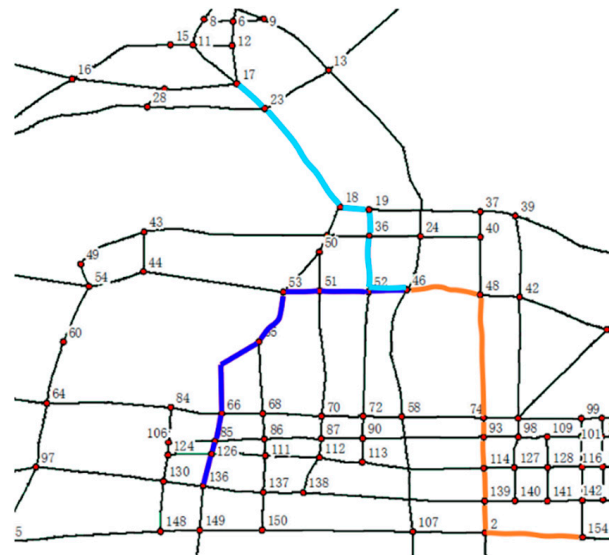


Figure 8. Rescue Paths from Rescue Point 17.

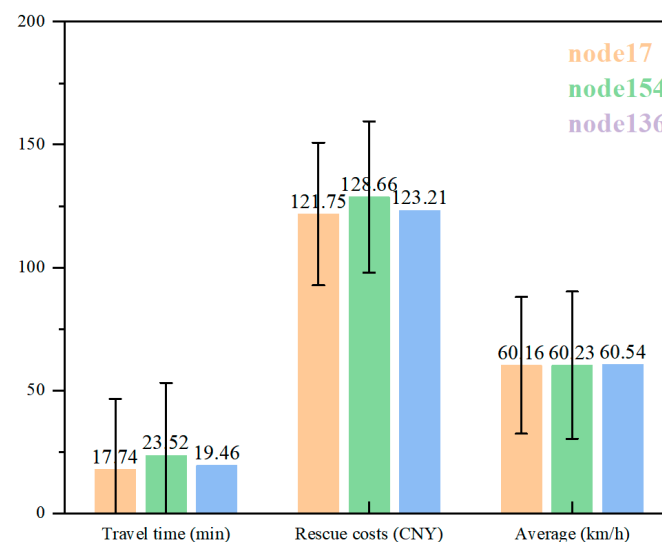


Figure 9. Comparison of Metrics.

From Figure 9, it is evident that Vehicle 1 has the shortest travel time and the lowest cost compared to the other vehicles. Therefore, when an accident occurs at Node 46, Vehicle 1 should be prioritized for dispatch. The actual route of the vehicle in Dongying City is: starting from the intersection of Country Road 009 and Provincial Road S227, traveling southeast along S227 for 621 m to National Road G516, continuing southeast along G516 for 8.9 km to Zhenxing Road, then east along Zhenxing Road for 1.3 km to Minfeng Avenue, heading south on Minfeng Avenue for 5.2 km to Tongxing Road, and finally east along Tongxing Road for 1.2 km to the accident point. This scheduling case demonstrates that the proposed model effectively addresses the issues of where to dispatch emergency vehicles and the optimal path planning.

To validate the superiority of the improved ACO algorithm, it was compared with Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and another improved ACO (MMAS). All algorithms were run 30 times on the same dataset. The results are shown in Table 3. One-way ANOVA and Tukey post hoc tests indicate that the proposed algorithm significantly outperforms others in rescue time and comprehensive performance index ($p < 0.05$).

Table 3. Performance Comparison of Different Algorithms.

Algorithm	Rescue Time (min) Mean $\pm$ SD	Rescue Cost (CNY) Mean $\pm$ SD	Comprehensive Index Mean $\pm$ SD	Significantly Better than Traditional ACO? ($p < 0.05$)
Traditional ACO	24.39 $\pm$ 2.12	150.23 $\pm$ 8.45	158.00 $\pm$ 12.34	–
Proposed Improved ACO	22.25 $\pm$ 1.78	121.75 $\pm$ 7.89	86.00 $\pm$ 9.21	Yes
Genetic Algorithm (GA)	25.67 $\pm$ 2.45	155.89 $\pm$ 9.32	165.34 $\pm$ 13.78	No
Particle Swarm Optimization (PSO)	23.98 $\pm$ 2.11	145.67 $\pm$ 8.97	142.56 $\pm$ 11.45	No
Max-Min Ant System (MMAS)	22.87 $\pm$ 1.95	130.45 $\pm$ 8.12	95.23 $\pm$ 10.12	Yes (but lower than Proposed ACO)

4.3. Scalability and Generalizability Analysis

To verify the applicability of the proposed framework to road networks of different scales, it was applied to data from Jinan and Qingdao city networks. The results show that the method maintains high dispatch efficiency and stability even in large-scale networks. Future work may extend this framework to multi-modal rescue systems (e.g., coordinated dispatch of drones and helicopters), further enhancing emergency response capabilities in complex environments.

5. Conclusions

In this study, a hybrid optimization framework for emergency vehicle dispatch in complex highway environments is proposed, which integrates logistic regression, BP neural networks, and an improved ant colony optimization (ACO) algorithm. This study makes three key contributions: First, environmental factors influencing accident severity are dynamically screened using logistic regression, enhancing the model’s adaptability to real-time conditions. Second, a BP neural network is employed to predict the spatial impact range of accidents, providing critical input for route planning. Third, the traditional ACO algorithm is enhanced through adaptive state transition rules and a pheromone reward–penalty mechanism, significantly improving convergence speed and global search capability.

Simulation experiments demonstrate that the proposed algorithm converges to a comprehensive performance index of 86 within only 8 iterations, compared to 158 after 2 iterations for the traditional ACO. Furthermore, comparative studies with other meta-heuristic algorithms—including genetic algorithm (GA), particle swarm optimization (PSO), and max–min ant system (MMAS)—confirm the superior performance of our approach in terms of rescue time, cost, and solution stability, with statistical significance validated through ANOVA and post hoc tests.

The model also incorporates a multi-objective optimization structure that balances rescue time, cost, and delay penalties, with weight coefficients determined via the analytic hierarchy process (AHP) and further evaluated through sensitivity analysis. The selected BP neural network architecture, with a single hidden layer of six neurons, was shown to achieve an optimal trade-off between prediction accuracy and computational efficiency after comparative trials with alternative structures such as LSTM and GRU.

Despite these advances, the study is subject to certain limitations. The case study is currently confined to a regional highway network, and although scalability tests in larger urban networks (e.g., Jinan and Qingdao) show promising results, broader validation across diverse geographical and traffic conditions is warranted. Additionally, the dispatch

model assumes the availability of sufficient vehicle resources and does not yet incorporate multi-modal transport coordination.

Future research will focus on extending the proposed framework to support integrated multi-modal emergency response systems, incorporating drones, helicopters, and ground vehicles for collaborative dispatch. The integration of deep reinforcement learning and real-time big data analytics also presents a promising direction for developing more adaptive and intelligent dispatch systems. To promote reproducibility and further development, the dataset and implementation code have been made publicly available.

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