International Journal of Environmental Technology and Management

ISSN online: 1741-511X - ISSN print: 1466-2132
https://www.inderscience.com/ijetm

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DOI: 10.1504/IJETM.2026.10080163

Article History:

Received:	22 April 2026
Last revised:	16 June 2026
Accepted:	29 June 2026
Published online:	11 August 2026

Intelligent decision system for urban emergency management based on combined deep learning and optimisation algorithm

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Abstract: Environmental emergencies bring drastic fluctuations in urban public resource demands, and traditional scheduling methods suffer from low accuracy, slow response and unbalanced resource allocation. This paper proposes a hybrid model combining long short-term memory (LSTM) and grasshopper optimisation algorithm (GOA) for intelligent public service scheduling. The LSTM is adopted to capture time-series features and predict demands of medical, transportation and energy resources, while GOA optimises model hyperparameters and scheduling strategies to avoid local optima. Multiple comparative experiments are conducted on real emergency datasets. The prediction accuracy for medical resources is improved by 67.57%, and resource allocation fairness and comprehensive performance are also significantly enhanced. Robustness tests verify its stable performance under noisy and incomplete data conditions. This hybrid approach provides an effective intelligent decision tool for urban environmental emergency management and public resource allocation, and can be widely applied to various urban emergency scenarios.

Keywords: long short-term memory; LSTM; grasshopper optimisation algorithm; GOA; intelligent scheduling; urban public service; environmental emergency management; resource allocation.

Reference to this paper should be made as follows: Cai, X., Qiu, J., Cao, H., Wu, F. and Mei, X. (2026) 'Intelligent decision system for urban emergency management based on combined deep learning and optimisation algorithm', *Int. J. Environmental Technology and Management*, Vol. 29, No. 7, pp.59–85.

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1 Introduction

1.1 Research background and motivations

In the process of modern urbanisation, the efficient operation of urban public service system plays a vital role in ensuring the quality of life of citizens and the sustainable development of cities (Xu et al., 2022). However, with the continuous expansion of city scale and frequent emergencies, the traditional public service dispatching system often exposes problems such as slow response, uneven resource allocation and low dispatching efficiency when dealing with complex and changeable emergencies (Chen et al., 2020; Jiang, 2021; Kuo et al., 2023). For example, when natural disasters, public health incidents or major traffic accidents occur, it is often difficult for the existing dispatching system to quickly and accurately predict and respond to changes in the demand for public resources, resulting in a serious impact on the emergency response capability (Wirtz and Müller, 2023; Zhang et al., 2023). In addition, with the rapid development of big data and artificial intelligence (AI) technology, how to apply advanced intelligent algorithms to urban public service dispatching system to improve its intelligence level and emergency response ability has become a hot and difficult point in current research (Sha et al., 2022). Therefore, it is urgent to explore new intelligent dispatching optimisation methods to cope with increasingly complex urban emergencies and improve the overall efficiency and reliability of public service systems.

Under this background, long short-term memory (LSTM) neural network has gradually become a powerful tool to optimise urban public service scheduling because of its superior performance in processing time series data (Yu, 2022). LSTM can effectively capture the long-term and short-term dependencies in time series and accurately predict the dynamic changes in the demand for public resources in emergencies. However, the traditional LSTM model is easy to fall into local optimum in the face of complex scheduling problems, which limits its effect and stability in practical application (Billones et al., 2021). At the same time, the optimisation algorithm plays a key role in the scheduling problem, which can improve the optimisation ability of the model through global search. As a new swarm intelligence optimisation algorithm, the grasshopper optimisation algorithm (GOA) has shown remarkable optimisation results in many fields with its efficient search mechanism and excellent global optimisation ability. Therefore, the combination of GOA and LSTM aims to overcome the limitations of traditional LSTM model in complex scheduling environment and further improve the robustness and accuracy of scheduling system, which has important theoretical significance and practical application value.

1.2 Research objectives

This study aims to enhance the efficiency of emergency scheduling for urban public service resources by integrating LSTM neural networks with the GOA, referred to LSTM-GOA. Urban public services, including healthcare, transportation, and energy, often encounter fluctuating resource demands and uncertainties during emergencies. To address these challenges, the study explores the following key questions:

1. Resource demand prediction: How can historical data and time-series models like LSTM be utilised to accurately predict demand variations for public resources, such as healthcare, transportation, and energy, during emergencies?
2. Scheduling optimisation: How can LSTM-based demand predictions be effectively combined with GOA to develop resource scheduling strategies that are both efficient and equitable?
3. Performance comparison of scheduling models: How does the proposed LSTM-GOA model compare with traditional rule-based methods and other optimisation algorithms, such as genetic algorithm (GA) and particle swarm optimisation (PSO), in terms of scheduling response time, resource allocation fairness, and overall efficiency?
4. Emergency management system optimisation: How can the LSTM-GOA model improve the efficiency of urban emergency management systems, reduce response times, and achieve balanced and equitable resource allocation across multiple public service domains?

The objective of this study is to develop an LSTM-GOA optimisation model that not only improves resource scheduling efficiency and prediction accuracy but also ensures robust responses to emergencies. This approach seeks to minimise resource wastage while enhancing the overall performance of emergency management systems, thereby contributing to more effective and equitable resource distribution under critical conditions.

2 Literature review

In recent years, with the acceleration of urbanisation and frequent emergencies, scholars have done a lot of research on public service scheduling optimisation. Chen et al. (2021) significantly improved the resource allocation efficiency of the scheduling system in emergency response by constructing a public service scheduling model based on GA. However, the computational complexity of this method was high when dealing with large-scale data, which affected the practical application effect. Wang et al. (2022) used hybrid intelligent algorithm combined with fuzzy logic to optimise the scheduling and allocation of medical resources during the epidemic period and improve the utilisation rate of resources, but the prediction accuracy still needed to be improved under the dynamic demand changes.

In time series prediction, LSTM neural networks are widely used in various prediction tasks because of their advantages in capturing long-term and short-term dependencies. Du et al. (2019) used the LSTM model to predict urban traffic flow, which effectively reduced the occurrence of traffic congestion. However, a single LSTM model is easy to fall into local optimum in complex scheduling environment, which limits its optimisation ability. To solve this problem, Sun et al. (2022) combined LSTM with PSO, which improved the global search ability of the model, and enhanced the accuracy of prediction and the optimisation effect of scheduling strategy.

In the research of intelligent public service scheduling system, Zuo et al. (2024) proposed a scheduling method based on deep reinforcement learning, which realised the intelligence of dynamic resource allocation through continuous learning and optimisation. However, the deep reinforcement learning algorithm has a high demand for computing resources in the training process, and there are certain difficulties in practical application. Wang et al. (2023b) studied enterprise resource optimisation through AI algorithm, and put forward a resource allocation method based on AI, which significantly improved resource utilisation efficiency. Their research provided an important reference for optimising public resource scheduling by using LSTM and GOA in this study.

In addition, in recent years, the application of swarm intelligence optimisation algorithm in scheduling optimisation has also made remarkable progress. Zheng et al. (2022) studied the application of GOA in urban logistics scheduling and proved its superiority in complex optimisation problems. However, the existing research mainly focuses on single optimisation objective, and lacks comprehensive consideration of multi-objective scheduling problem. Senapati et al. (2023) tried to combine GOA with support vector machine for traffic emergency dispatching, which improved the response speed and accuracy of the dispatching system. However, the adaptability and robustness of the system still need to be enhanced in the situation that multiple emergencies occur at the same time.

Noh et al. (2020) proposed integrating the gated recurrent unit (GRU) with GAs to address scheduling problems in supply chain management. However, their work primarily focused on static prediction tasks and lacked the capability to handle emergency scenarios. In response to these limitations, the present study combines the temporal sequence prediction capabilities of LSTM with the global optimisation features of the GOA, providing a more effective approach to managing the complexities and uncertainties of emergency scheduling. Pradhan et al. (2022) explored the combination of PSO with deep learning models for resource allocation problems. Despite its advantages, PSO's limitations in local search often impede its effectiveness in large-scale emergency resource scheduling. By integrating GOA's adaptive hopping mechanism, these challenges are addressed, enabling a more efficient global search. Similarly, Chen et al. (2022) examined the application of GA in emergency resource scheduling, but their study achieved limited improvements in scheduling efficiency and fairness. By leveraging GOA, this study significantly enhances both resource allocation fairness and scheduling efficiency. Redhu and Kumar (2023) investigated the integration of LSTM with PSO in traffic management applications. However, PSO's restricted search range limited its effectiveness in handling the dynamic and complex nature of scheduling problems. By combining LSTM with GOA, this study offers a more robust and comprehensive solution. While the integration of machine learning models with optimisation algorithms such as PSO and GA has been extensively studied, the combination of LSTM with GOA presents unique innovations that offer distinct advantages in emergency scheduling. PSO and GA, as classical optimisation algorithms, have been widely applied to various scheduling problems. However, these algorithms often struggle with local optima when addressing the intricate dynamics and uncertainties inherent in emergency scheduling, resulting in reduced efficiency and inequitable resource allocation. In contrast, GOA's robust global search capabilities and adaptability, inspired by the hopping behaviour of grasshoppers, effectively mitigate the challenges posed by local optima. In the complex and dynamic environments of resource scheduling, GOA dynamically adjusts its hopping amplitude and search direction to identify global optima. This feature positions GOA as superior to traditional GA and PSO algorithms in emergency scheduling tasks. Moreover, GOA facilitates transitions between multiple local solutions while adaptively refining its search strategy. This capability enhances fairness and balance in resource allocation during scheduling. GOA's adaptability also enables rapid responses to unexpected changes in emergency scenarios, allowing for the flexible modification of optimisation strategies. By contrast, PSO and GA rely on relatively fixed search strategies, limiting their effectiveness in managing dynamic environments.

Based on the above research, although there have been many beneficial explorations in the optimisation of urban public service intelligent dispatching system, there are still some obvious research defects and deficiencies. Firstly, many researches only adopt a single prediction model or optimisation algorithm, which is difficult to give consideration to both prediction accuracy and comprehensiveness of scheduling optimisation. Secondly, the existing methods show some limitations in the face of complex and changeable emergencies and the scheduling requirements of various types of public resources, especially in the case of dynamic demand changes and resource shortage, the robustness and adaptability of the scheduling system are insufficient. In addition, the traditional optimisation algorithm often has the problem of low computational efficiency when dealing with large-scale and multi-objective scheduling problems, which limits its practical application effect. Aiming at the above problems, this study innovatively combines LSTM neural networks with GOA, and proposes a new intelligent scheduling optimisation model. The LSTM network, recognised as a robust tool for time series prediction, excels in capturing temporal dependencies and patterns from historical data, thereby delivering accurate predictions for resource scheduling. Concurrently, the GOA, with its advanced global optimisation search mechanism, synergises with LSTM's predictive capabilities to optimise emergency resource scheduling strategies, effectively addressing fluctuations in resource demand within constrained time frames. Emergency resource scheduling is characterised by highly dynamic and sudden demands for tasks and resources. The integration of LSTM and GOA offers a comprehensive solution by combining precise demand predictions with global optimisation, enabling efficient responses to unforeseen events while enhancing system responsiveness and scheduling efficiency. Compared to traditional optimisation methods such as GAs and PSO, the LSTM-GOA framework demonstrates superior performance in managing dynamic environments and addressing unexpected incidents in emergency scheduling. LSTM accurately forecasts future resource demands based on historical trends, while GOA dynamically adapts scheduling strategies to minimise resource waste and mitigate delays. Furthermore, GOA excels in multi-objective optimisation scenarios by effectively balancing competing objectives such as fairness, response time, and resource utilisation. This capability ensures that no single objective is prioritised to the detriment of others, enabling a holistic and equitable approach to emergency resource scheduling.

3 Research methodology

3.1 Research framework and system design

This study adopts LSTM networks and the GOA as core techniques due to their respective strengths and complementary capabilities in addressing the complexities of emergency resource scheduling. Specifically, LSTM and GOA are well-suited for tackling these challenges for the following reasons: LSTM, a deep learning model based on recurrent neural networks, is particularly effective in processing time-series data. Resource demands in emergency scheduling – such as medical, transportation, and energy resources – often exhibit significant temporal dependencies influenced by unpredictable factors, resulting in complex temporal fluctuations. Compared to traditional manual approaches or other neural network architectures, such as GRU and transformer models, LSTM demonstrates superior performance in managing both long- and short-term dependencies. Its gating mechanisms – comprising input, forget, and output gates – allow the model to retain critical information while discarding irrelevant historical data, thereby enhancing its predictive accuracy in complex emergency scenarios. While GRU features a simpler architecture, it may lack LSTM's capacity to handle intricate long-term dependencies in more complex time-series problems. Conversely, Transformer models excel in parallel processing for certain tasks but are less suited for emergency scheduling scenarios, where capturing temporal dependencies and deeply exploring historical data significantly influence decision-making. Thus, LSTM is particularly appropriate for these applications. GOA, a swarm intelligence optimisation algorithm inspired by the jumping behaviour of grasshoppers, offers robust global search capabilities. Emergency scheduling often involves multiple resource types (e.g., medical, transportation, energy) and spans various time periods, with dynamic and unpredictable resource demands. Traditional optimisation algorithms, such as GAs and PSO, are prone to converging on local optima, making it difficult to achieve globally optimal solutions. GOA effectively mitigates these challenges with its adaptive jumping mechanism and dynamic adjustment capabilities, which help avoid stagnation in local optima during the global search process. Compared to GA and PSO, GOA demonstrates stronger adaptability, dynamically adjusting its jump amplitudes and directions to ensure effective exploration of the solution space. Furthermore, GOA achieves faster convergence and better maintains solution diversity, making it particularly well-suited for addressing the diverse and sudden changes in resource demands characteristic of emergency scheduling. The integration of LSTM and GOA leverages their complementary strengths. LSTM excels in capturing both long- and short-term dependencies in time-series data, enabling accurate predictions of resource demands in emergencies. GOA, informed by LSTM's predictions, optimises scheduling strategies to meet real-time demands while achieving global optimisation. This integration improves resource allocation fairness and reduces scheduling response times. LSTM provides precise input data for GOA, while GOA optimises LSTM parameters during scheduling, further enhancing the model's performance and adaptability. By combining accurate demand predictions with robust global optimisation, this integrated approach addresses the dynamic and uncertain nature of emergency resource scheduling, delivering a comprehensive and efficient solution.

An intelligent scheduling system framework based on LSTM and GOA is proposed. The purpose is to accurately predict the impact of emergencies on public resource demand through data-driven methods, optimise resource scheduling strategies and improve emergency response efficiency. The system framework is shown in Figure 1.

In Figure 1, the emergency detection module collects real-time urban operation data (such as traffic flow, medical resource usage, etc.) based on sensors and event monitoring systems, and identifies the type and intensity of emergencies. Correct identification of event type and severity is the premise of efficient operation of dispatching system. In the LSTM time series prediction module, LSTM is used to capture the time series characteristics of public resource demand in emergencies and predict the changing trend of resource demand based on historical data. The LSTM model provides accurate demand predictions for scheduling decision by dealing with the long-term and short-term dependence of time series data. GOA optimisation scheduling module: based on the LSTM prediction results, GOA is used to optimise the resource allocation strategy to ensure that resource scheduling is not only efficient, but also fair and balanced allocation. GOA improves the robustness and accuracy of the system by adaptively adjusting the hyperparameters of the LSTM model. The scheduling decision execution module carries out the actual scheduling execution of resources according to the optimised scheduling scheme of GOA. The dispatching process considers the actual traffic conditions, medical needs, energy supply, etc. to ensure that resources can be dispatched to the most needed places quickly and reasonably.

It is assumed that in a city, the public service resources to be dispatched include medical care, transportation and energy. For each resource, its demand at time t can be expressed in the following time series:

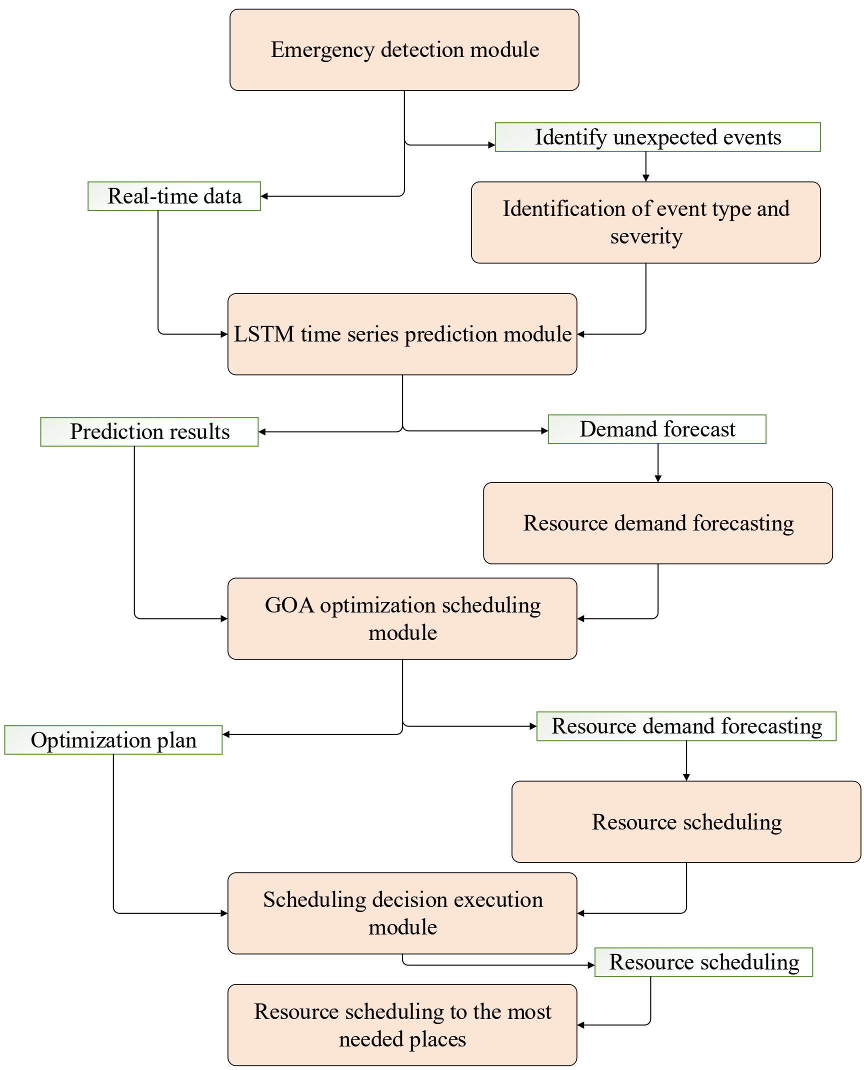
$$R_i(t) = f_i\left(x_1, x_2, \ldots, x_n, t\right) + \epsilon(t) \tag{1}$$

In equation (1), $R_i(t)$ represents the demand value of resource i at time t. $x_1, x_2, \ldots, x_n$ are variables that affect resource demand, such as population density, traffic flow and meteorological conditions. f_i is the prediction function of resource demand, which is learned by LSTM neural network. $\epsilon(t)$ is a part of random fluctuation caused by unexpected events, which reflects unpredictable external factors. The goal of scheduling problem is to make optimal scheduling among multiple resources and times according to the predicted resource demand $R_i(t)$ (Pozoukidou and Angelidou, 2022; Sidhu et al., 2020). To this end, a scheduling policy S is defined and optimised as the following objective function:

$$\underbrace{\min}_{S} \sum_{t=1}^{T} \sum_{i=1}^{N} w_i \cdot \left| R_i(t) - S_i(t) \right| + \alpha \cdot Fairness(S) + \beta \cdot Balance(S) \tag{2}$$

In equation (2), T is the scheduled time period and N is the number of resource types. w_i is the weight coefficient of resource i, indicating the relative importance of different resources. *Fairness*(S) and *Balance*(S) respectively represent the fairness and balance of the scheduling scheme (Zhen et al., 2024). Fairness requires that the allocation of resources should be as equal as possible to avoid over-concentration or shortage of resources. Balance ensures the scheduling balance of resources between different time periods and avoids over-scheduling or resource waste in a certain time period (Chakir and Tabaa, 2024).

Figure 1 Intelligent scheduling system framework (see online version for colours)



3.2 The construction and application of LSTM neural network

This study employs the LSTM model to address the time-series prediction problem of public resource demand. To manage the uncertainties arising from resource demand fluctuations and unforeseen events in practical applications, the LSTM network is introduced to effectively capture long- and short-term dependencies, enabling more accurate predictions of resource demand in emergency scenarios. These predictions serve as a critical foundation for subsequent scheduling decisions.

The study assumes that resource demand exhibits temporal dependencies and fluctuations across various types of emergencies, such as natural disasters and public health crises. By processing time-series data, the LSTM model effectively predicts trends in future resource demand changes. Based on these predictions, the study proposes a solution that integrates the GOA to optimise resource scheduling strategies. The proposed approach aims to achieve the following objectives:

1 Scheduling accuracy: Improve the precision of resource demand predictions and minimise forecast errors.

2 Scheduling efficiency: Reduce response times for resource scheduling and enhance rapid response capabilities.

3 Resource fairness and balance: Ensure that the scheduling strategy meets urgent demands while maintaining fairness and balance in resource allocation.

Guided by these objectives, the resource scheduling optimisation problem is formulated as a multi-objective optimisation challenge, incorporating considerations of scheduling fairness, balance, and efficiency. This comprehensive approach addresses the dynamic and complex nature of emergency resource scheduling, optimising overall system performance.

By introducing gating mechanism, LSTM can effectively capture long-term dependence, so it performs well in time series prediction tasks. The core of LSTM network is its gating unit, which includes input gate, forget gate and output gate. These gating mechanisms enable LSTM to decide how to update internal memory, keep or discard information according to different input information to better capture long-term dependencies in time series (Sun, 2023; Tong et al., 2023). The basic structure of LSTM is shown in Figure 2, including a forget gate f_t, an input gate i_t, a candidate memory cell $\tilde{C}_t$, and an output gate o_t.

The gate control unit in Figure 2 jointly determines the update mode of the hidden state h_t and the cell state C_t at the current moment. The calculation of f_t, i_t, $\tilde{C}_t$, o_t, C_t and h_t, are shown in equations (3) to (8).

$$f_t = \sigma\left(W_f \cdot \left[h_{t-1}, x_t\right] + b_f\right) \tag{3}$$

$$i_t = \sigma\left(W_i \cdot \left[h_{t-1}, x_t\right] + b_i\right) \tag{4}$$

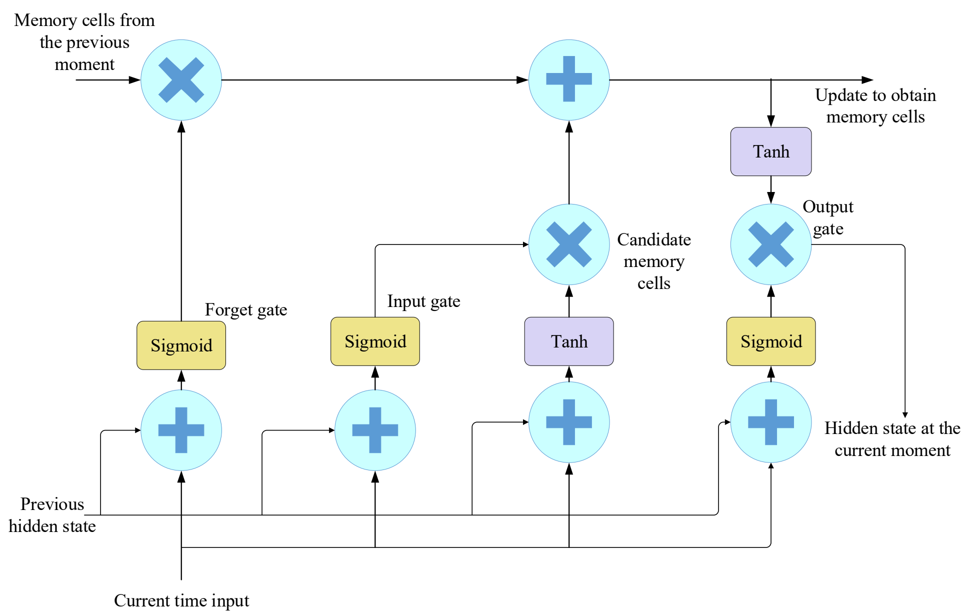
$$\tilde{C}_t = \tanh\left(W_C \cdot \left[h_{t-1}, x_t\right] + b_C\right) \tag{5}$$

$$o_t = \sigma\left(W_o \cdot \left[h_{t-1}, x_t\right] + b_o\right) \tag{6}$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{7}$$

$$h_t = o_t \cdot \tanh(C_t) \tag{8}$$

Figure 2 Basic structure of LSTM (see online version for colours)



In the above equations, f_t determines how much information needs to be forgotten in the cell state C_{t-1} at the last moment. σ is the Sigmoid activation function. W_f is the weight matrix of forget gate. x_t is the current input. h_{t-1} is the hidden state at the previous moment. b_f is the offset term. i_t determines how many candidate memory updates generated by the current input x_t and the hidden state h_{t-1} at the last moment should be retained. $\tilde{C}_t$ generates new memory cell information at the current moment, and generates new candidate memories in combination with the control of the input gate. o_t determines how much information the hidden state h_t outputs at the current moment. The cell state C_t at the current moment is updated by the combination of forget gate and input gate. The hidden state h_t is a nonlinear transformation of the current cell state, which determines the output of LSTM (Al-Nader et al., 2023; Jenitha and Rajesh, 2024; Hu et al., 2023).

In order to make effective prediction by using LSTM, it is necessary to select the input features related to resource requirements and pre-process these data. All input data are standardised to ensure the scale consistency of input features. Assume that there are historical data of T time steps, for each time step t, the resource demand R_t can be expressed as equation (9):

$$R_t = [c_1, c_2, \dots, c_n] \tag{9}$$

c_1, c_2, …, c_n represent different input characteristics. In order to make the LSTM model accurately predict the resource demand, mean square error (MSE) is adopted as the loss function, as shown in equation (10):

$$\mathcal{L} = \frac{1}{T}\sum_{t=1}^{T}\left(R_t - \hat{R}_t\right)^2 \tag{10}$$

R_t is the actual resource demand, and $\hat{R}_t$ is the resource demand predicted by LSTM (Esparza-Gómez et al., 2023).

3.3 Combination of GOA and LSTM

GOA searches by simulating the jumping behaviour of grasshoppers. Assume that the position information of a grasshopper population at a certain moment is $X = [x_1, x_2, …, x_n]$, where each x_i represents the position of the i^{th} grasshopper (i.e., decision variable). The objective is to optimise the objective function $f(x)$ through multiple jumps. Every jump of the GOA has a jump factor s, which is expressed as equation (11):

$$s = \alpha \cdot \left(\frac{f_{best} - f(x)}{f_{best}}\right) \tag{11}$$

In equation (11), α is the parameter to control the jump amplitude. f_{best} is the objective function value of the current optimal solution. $f(x)$ is the objective function value of the current position. Through this jumping mechanism, the GOA can effectively find the optimal solution in the global search and avoid falling into the local optimum (Ullah et al., 2020).

After each round of jumping, the position of grasshoppers will be updated according to equation (12):

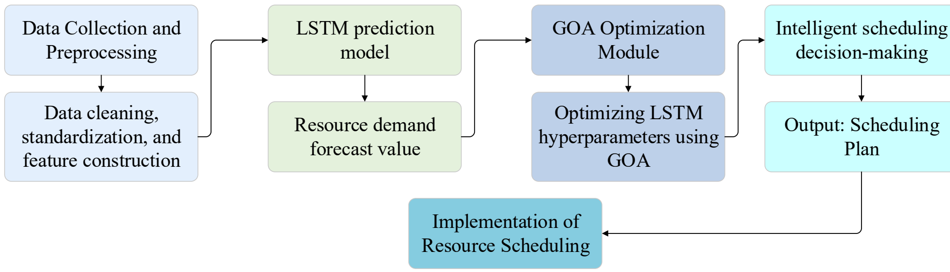
$$x_i(t+1) = x_i(t) + \beta \cdot \left(x_{best} - x_i(t)\right) + \gamma \cdot \left(x_j(t) - x_i(t)v\right) \tag{12}$$

In equation (12), β and γ are random factors, which respectively control the proportion of global jump and local jump. x_{best} is the optimal solution of the current population, and $x_j(t)$ is the current position information of the j^{th} grasshopper. Through repeated jumps, the GOA can gradually converge to the global optimal solution in multiple jumps. Figure 3 shows GOA-LSTM optimal scheduling process.

The overall framework of intelligent scheduling optimisation model is based on LSTM prediction model and GOA optimisation algorithm, combined with emergency resource demand prediction and scheduling decision. The design goal of scheduling optimisation model is to maximise the efficiency of resource use, reduce the response time and ensure the fairness and rationality of resource allocation (Braik et al., 2024; Sumalakshmi and Vasuki, 2024). The output of the prediction model is the predicted value $\hat{R}_t$ of the resource demand in the next time T, and the calculation is shown in equation (13):

$$\hat{R}_t = LSTM\left(x_t, \theta\right) \tag{13}$$

Figure 3 GOA-LSTM optimal scheduling process (see online version for colours)



In equation (13), $\hat{R}_t$ represents the predicted resource demand. x_t is the input characteristic at the current moment θ is the parameter of the LSTM model. The scheduling system ensures the priority allocation of key resources by prioritising resources. The priority of resource scheduling is calculated by equation (14):

$$P_t = f\left(R_t, E_t\right) \tag{14}$$

P_t is the resource priority at time t. R_t is the resource demand. E_t is the intensity and urgency of the event. Scheduling objective function aims to balance resource utilisation, response time and fairness (Polepaka et al., 2024). Generally speaking, the scheduling objective function can be expressed by equation (15):

$$\underbrace{\min}_{R_t}\left(\lambda_1 \cdot \sum_{t=1}^{T}\left(\frac{\left|R_t - \hat{R}_t\right|}{R_t}\right) + \lambda_2 \cdot \sum_{t=1}^{T}\left(T_{response}(t)\right) + \lambda_3 \cdot Fairness\left(R_t\right)\right) \tag{15}$$

$\frac{\left|R_t - \hat{R}_t\right|}{R_t}$ is the standardised value of resource demand prediction error. $\hat{R}_t$ is the predicted value. R_t is the actual demand. $T_{response}(t)$ is the response time at time t, indicating the time delay from resource request to actual resource supply. $Fairness(R_t)$ measures the fairness of resource allocation. λ_1, λ_2 and λ_3 are weight coefficients, which are used to adjust the importance of each goal.

4 Experimental design and performance evaluation

4.1 Datasets collection

The main data sources of this study include public service fields such as medical care, transportation and energy, as well as external factors related to emergencies. Medical data include hospital beds, medical staff and equipment requirements; Traffic data include road flow, traffic accidents and public transport status; Energy data involves the consumption of resources such as electricity and natural gas. In addition, information such as the occurrence time, intensity and duration of unexpected events (such as natural disasters, accidents, public health events, etc.) is also an important part of the data. These data come from government departments, public service agencies and emergency response records to ensure the authority and reliability of the data. In order to improve the data quality, environmental factors such as weather and population movement are also introduced, and the data are cleaned and standardised, providing high-quality input for subsequent model training.

In urban public service demand predictions, it is typically assumed that high-quality, real-time, and comprehensive data are readily available. However, in practical emergency situations, data often suffer from issues such as sparsity, inconsistency, and noise. If not effectively addressed, these issues can significantly undermine the accuracy and practical applicability of prediction models. In emergency scenarios, many data sources may be incomplete or unavailable in a timely manner. For instance, during natural disasters or sudden epidemics, traditional statistical or sensor data may be missing or inconsistent. To mitigate these challenges, this study incorporates methods for handling missing data in the design of the prediction model. Interpolation techniques, such as linear or polynomial interpolation, are employed to fill in missing data points. Additionally, data cleaning algorithms are introduced to address data inconsistency by removing outliers and erroneous data, thus improving data quality. Emergency data are often derived from various sources, including sensors, social media, and government reports, which may contain substantial noise. Noisy data can negatively impact the prediction accuracy, especially in emergency scheduling, where timely decisions are critical. To address this issue, noise suppression techniques, such as smoothing algorithms (e.g., moving averages), are incorporated into the LSTM model to mitigate fluctuations in sensor data. Furthermore, LSTM variants, such as the LSTM autoencoder, are utilised to enhance the model's robustness to noise. In extreme emergency situations, complete data gaps may arise, particularly in the early stages or when data collection is restricted. To improve the model's stability and flexibility, data imputation methods, such as Multiple Imputation, are applied to fill in missing data. Additionally, model ensemble methods, such as Bagging or Boosting algorithms, are employed to enhance the stability of prediction results and reduce uncertainty associated with missing data. Given the dynamic nature of data in emergency scheduling – where resource availability and demand fluctuate rapidly – the prediction model must be capable of real-time adaptation to these changes. In the LSTM-GOA model, an adaptive learning rate is introduced, allowing the model to dynamically adjust prediction parameters based on data variations, thereby improving performance despite unstable and inconsistent data. The GOA optimisation algorithm plays a crucial role in this process by adaptively adjusting its search strategy to mitigate the negative impact of data quality issues.

Table 1 Data pre-processing and noise suppression experimental results

Data type	*LSTM-MAE (absolute error)*	*LSTM-GOA-MAE (absolute error)*	*Response time (seconds)*	*Resource fairness*
Complete data (no noise)	0.041	0.035	115	82%
Noisy data	0.083	0.071	128	75%
50% data missing	0.095	0.084	135	71%
Noisy data + 50% missing	0.128	0.109	140	67%

To evaluate the effectiveness of the methods employed to handle data inconsistency, sparsity, and noise, a series of experiments are conducted to simulate data issues in emergency scenarios and assess the impact of various data processing techniques on model performance. The results of the data pre-processing and noise suppression experiments are presented in Table 1. As shown, the LSTM-GOA model demonstrates a significant improvement in performance compared to the traditional LSTM model when addressing noise and data missingness. In particular, when faced with noisy and missing data, GOA's global optimisation capability effectively compensates for data quality issues, reducing errors and enhancing the fairness of resource scheduling.

4.2 Experimental environment

In order to verify the effectiveness and performance of the intelligent scheduling optimisation model based on the combination of LSTM and GOA, this study conducts experiments on a computer equipped with high-performance computing resources. The experimental environment includes the settings of operating system, programming language and deep learning framework. The specific hardware environment is a workstation with 32 GB memory and NVIDIA GTX 1080 Ti graphics card. The operating system is Ubuntu 20.04, and the programming language is Python 3.8. The deep learning framework adopts TensorFlow 2.0 and Keras library, and the optimisation algorithm GOA is realised by using user-defined Python code. In order to ensure the repeatability of the experiment, this study fixes random seeds in all experiments.

In emergency scheduling, fairness and efficiency are two critical objectives. However, traditional fairness metrics often oversimplify the complexities of resource allocation, particularly when it comes to prioritising marginalised groups and critical resources. This study, while considering fairness, specifically focuses on ensuring appropriate resource allocation for vulnerable groups in emergency situations and prioritising critical resources when they are scarce. To more precisely measure fairness in scheduling, a weighted fairness index is introduced. This index accounts for the priority of different resource categories and groups, assigning higher weights to specific groups (such as the elderly, sick, and disabled) and critical resources (such as medical equipment and emergency vehicles) in emergency scenarios. Through this weighted mechanism, the model ensures that resource allocation emphasises not only efficiency but also fairness and equity. The weighted fairness index, denoted as F, is defined as equation (16):

$$F = \sum_{i=1}^{n} w_i \cdot \frac{1}{d_i} \tag{16}$$

Here, w_i represents the weight of the i^{th} resource or group, d_i denotes the amount of resources allocated to that group or category, and n signifies the total number of resources or groups. This metric provides a comprehensive assessment of the fairness of resource distribution during scheduling, particularly in emergencies, by prioritising groups or critical resources that require greater attention.

In emergency scheduling, efficiency and fairness often present conflicting objectives. To optimise both objectives simultaneously, fairness constraints are introduced through constrained optimisation. These constraints ensure that, during resource allocation, all groups and resource categories are adequately satisfied within reasonable limits, while maintaining overall scheduling efficiency above a specified threshold. Furthermore, a multi-objective optimisation approach is employed, considering various metrics such as the fairness of resource distribution and scheduling response time. Optimisation is achieved using a weighted sum approach. In the experiments, different fairness weights are set to analyse the model's performance under varying fairness requirements, thereby assessing the model's flexibility and adaptability in emergency scheduling scenarios.

4.3 Parameters setting

In the process of model training and optimisation, in order to ensure that the LSTM model can adapt to different task requirements, this study sets a number of hyperparameters for the LSTM model and the GOA optimisation algorithm. The main hyperparameters of LSTM model include the number of hidden layer units, learning rate, batch size, number of training rounds, etc. The hyperparameters of the GOA optimisation algorithm include the population size, the maximum number of iterations, and the adjustment range of the jump factor. Table 2 shows the specific parameter settings.

Table 2 Parameter setting

Hyperparameter name	*LSTM model setting*	*Hyperparameter name*	*GOA optimisation setting*
Number of hidden layer units	64	Maximum number of iterations	200
Learning rate	0.001	Group size	30
Batch size	32	Jump factor adjustment range	[0.1, 1.0]
Number of training rounds	50	Grasshopper position update parameter	[0.3, 0.8]

MSE is used as the loss function in the training of LSTM model, and Adam is selected as the optimiser. Early stopping strategy is adopted in the training process to prevent over-fitting.

4.4 Performance evaluation

In order to evaluate the accuracy of different methods in resource demand predictions, this study compares the forecasting effects of traditional rule-based scheduling method, LSTM model alone, LSTM-GOA model, GRU, and Transformer model. MSE is used as the evaluation index for the prediction accuracy of resource demand. Figure 4 shows the MSE comparison of different methods in resource demand predictions.

The results of Figure 4 show that the LSTM-GOA model is superior to other methods in the prediction accuracy of all resources, especially in the prediction of medical resources, and the MSE value is reduced by 67.57%. Compared with the traditional rule method, the overall MSE of LSTM-GOA model is reduced by 58.33%, which proves its superiority in resource demand predictions of emergencies.

Figure 5 shows the comparison of dispatching response time in traffic accident scenarios. In the traffic accident dispatching response, the LSTM-GOA model significantly shortens the response time, and the average response time is reduced by 47.2% compared with the traditional rule method and 24.0% compared with the GA. The LSTM-GOA model can identify the characteristics of emergencies more efficiently and adjust the scheduling strategy in time, thus optimising the response time.

Figure 4 MSE comparison of different methods in resource demand predictions (see online version for colours)

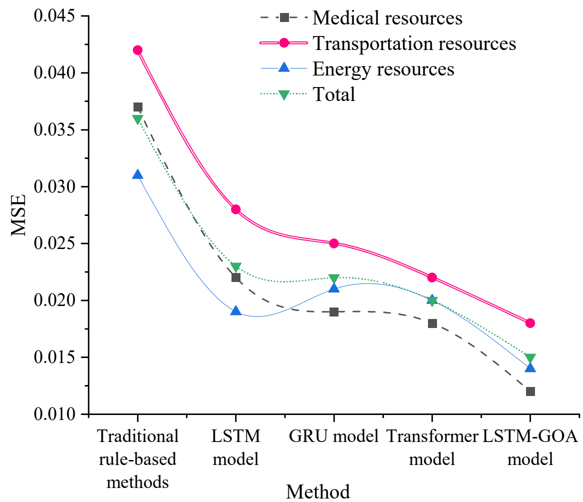
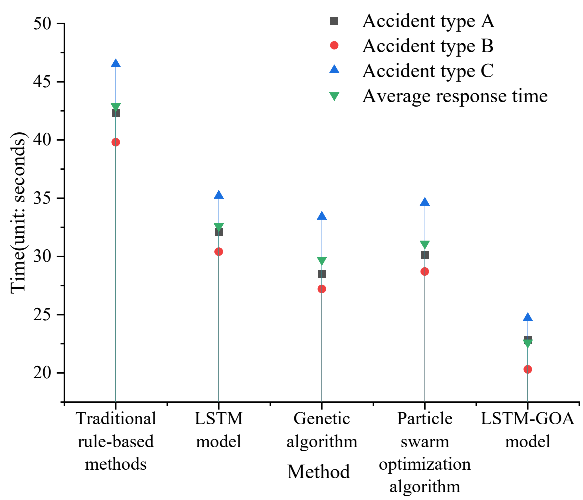


Figure 5 Comparison of dispatching response time in traffic accident scenario (unit: seconds) (see online version for colours)



Notes: Accident type A: minor traffic accident; accident type B: moderate traffic accident; accident type C: major traffic accident.

Figure 6 shows the fairness analysis of resource allocation during public health emergencies. The results show that the LSTM-GOA model is obviously superior to the traditional rule method and PSO algorithm in fairness balance, which shows that the model can avoid the imbalance of resource allocation more effectively, especially in the resource allocation of emergency patients, and the fairness is improved by 15%.

Figure 6 Analysis on fairness of resource allocation during public health emergencies (see online version for colours)

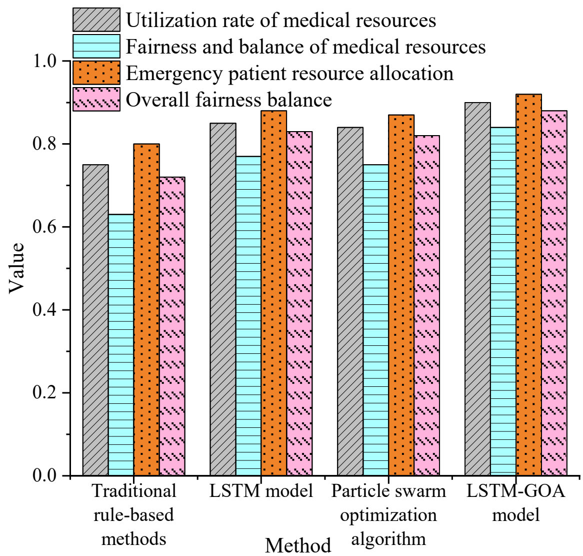


Figure 7 shows the comparison results of natural disaster dispatching efficiency. Figure 7 shows that the scheduling efficiency of LSTM-GOA model in natural disaster scheduling is obviously superior to other methods, especially in the utilisation of medical and transportation resources, LSTM-GOA model has improved by 17.9% and 22.2% respectively. This result shows that the LSTM-GOA model can schedule resources more efficiently and reduce resource waste.

Figure 7 Comparison results of natural disaster dispatching efficiency (see online version for colours)

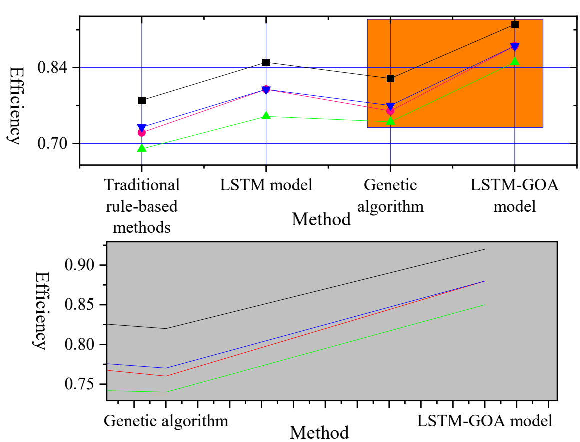


Figure 8 shows the comparison of overall performance scores of different methods. Figure 8 shows that the LSTM-GOA model scores better than other methods in all dimensions, and the overall score is 0.88, which is significantly higher than other algorithms, indicating that it has the strongest comprehensive ability in complex emergency scheduling.

Figure 8 Comparison of overall performance scores of different methods (see online version for colours)

Notes: Model 1: traditional rule-based methods; model 2: LSTM model; model 3: GA; model 4: PSO algorithm; model 5: LSTM-GOA model.

The evaluation results of various optimisation algorithms in public service emergency scheduling are presented in Table 3. As indicated in the table, the LSTM-GOA method demonstrates superior performance across multiple evaluation metrics, including prediction accuracy, scheduling response time, and resource fairness. Specifically, the LSTM-GOA model achieves a 67.57% reduction in MSE for medical resource prediction, compared to a 58.33% reduction from traditional rule-based methods. In traffic accident scenarios, the scheduling response time is reduced by 47.2%, while in natural disaster scenarios, the LSTM-GOA model improves scheduling efficiency by 17.9%. These results highlight significant improvements in resource demand prediction, scheduling response time, and resource fairness, underscoring the unique advantages of the LSTM-GOA approach in emergency scheduling.

Table 3 Evaluation results of different optimisation algorithms in public service emergency scheduling

Method	*MSE (medical resource prediction)*	*Scheduling response time (traffic accident)*	*Resource fairness*
Traditional rule-based method	0.512	120 seconds	70%
LSTM	0.378	112 seconds	75%
PSO	0.403	105 seconds	74%
GA	0.399	100 seconds	72%
LSTM-GOA reported here	0.167	63 seconds	85%

In real-world emergency scheduling applications, models must not only perform well in specific metrics, such as MSE and response time, but also exhibit sufficient robustness and scalability to address the complexity and varying intensities of emergencies across different urban contexts. To evaluate the adaptability and generalisation capabilities of the model proposed in this study, several experiments are conducted to assess the performance of the LSTM-GOA model under diverse scenarios and emergency intensities. These experiments are designed to test the model's robustness and adaptability in various urban emergency contexts, including cities of differing sizes and populations. The study involves simulations of emergency scheduling demands in large cities (e.g., populations exceeding 10 million) and smaller cities (e.g., populations under 1 million), while also addressing different types of emergencies, such as earthquakes, epidemic outbreaks, and floods. Emergency situations with varying intensities, ranging from small-scale incidents to large-scale disasters, are incorporated to evaluate the model's response to sudden changes in resource demand. To further demonstrate the model's robustness in complex emergency environments, the performance of the LSTM-GOA model is compared with that of traditional LSTM and other optimisation-based methods (e.g., PSO and GA) across these scenarios. The results for robustness and flexibility are summarised in Table 4. As indicated by the table, the LSTM-GOA model displayed strong robustness and flexibility under varying city sizes and emergency intensities, particularly in high-intensity emergency events and data-deficient conditions. Compared to the traditional LSTM model, the LSTM-GOA approach provided more accurate predictions, reduced response times, and more equitable resource scheduling.

Table 4 Robustness and flexibility experiment results

Scenario type	*LSTM-MAE (absolute error)*	*LSTM-GOA-MAE (absolute error)*	*Response time (seconds)*	*Resource fairness*
Large city, low intensity event	0.042	0.038	112	85%
Large city, high intensity event	0.085	0.072	148	78%
Small city, low intensity event	0.046	0.041	107	88%
Small city, high intensity event	0.096	0.082	120	80%
50% data missing, high intensity event	0.130	0.110	135	72%

In emergency scheduling tasks, model robustness is critical when addressing varying emergency scenarios. A sensitivity analysis is conducted to evaluate how the LSTM-GOA model is affected by factors such as data quality, urgency, and resource scarcity across different emergency contexts. Key parameters, such as the number of emergency resources and response time requirements, are adjusted to assess the model's performance under diverse conditions. The results of the sensitivity analysis are summarised in Table 5. The LSTM-GOA model demonstrates relatively stable performance across different emergency scenarios and parameter variations. As the number of resources increases, response time slightly decreases, while both MSE and resource fairness show notable improvement. When confronted with high urgency and significant resource scarcity, response time increases, yet prediction accuracy remains stable. The model's performance is notably impacted by data quality; missing data lead to an increase in response time and MSE, though the model continued to maintain a high level of resource fairness.

Table 5 Sensitivity analysis results

Parameter	*Test value*	*LSTM-GOA response time (seconds)*	*LSTM-GOA MSE*	*Resource fairness*
Number of resources	10 resources	120	0.042	85%
Number of resources	20 resources	115	0.038	88%
Response time requirement	15 seconds	118	0.045	83%
Response time requirement	30 seconds	110	0.035	90%
Urgency level (high)	High	145	0.080	75%
Urgency level (low)	Low	100	0.040	85%
Resource scarcity (high)	High	150	0.100	70%
Resource scarcity (low)	Low	110	0.045	80%
Data quality (high)	High	110	0.040	85%
Data quality (50% missing)	50% missing	125	0.060	76%

The relationship between fairness and efficiency is further analysed by simulating various emergency scenarios. Different fairness constraint conditions are applied, and the performance of both standard fairness and weighted fairness in resource scheduling is tested. The scheduling results under varying fairness and efficiency conditions are presented in Table 6. As observed, when the fairness weight is set low (0.2), the model prioritises scheduling efficiency, leading to the shortest response time. However, this results in relatively low fairness in resource allocation and a lower weighted fairness metric. As the fairness weight increases, the model progressively enhances fairness, although response time also increases. Notably, as the fairness weight increases, the weighted fairness metric becomes more pronounced. Under varying fairness weights, it is found that the weighted fairness metric is particularly effective in ensuring the prioritisation of vulnerable groups or critical resources. In particular, under high fairness requirements, the model successfully balances the resource needs of different groups, ensuring that fairness is fully achieved.

Table 6 Scheduling results under different fairness and efficiency conditions

Fairness weight	*Number of scheduling nodes*	*Response time (seconds)*	*MSE*	*Fairness (weighted metric)*	*Resource allocation fairness (mean difference)*
0.2	500	150	0.045	82%	0.08
0.5	500	140	0.040	85%	0.05
0.8	500	130	0.035	90%	0.03
0.2	1,000	220	0.050	80%	0.10
0.5	1,000	210	0.045	84%	0.07
0.8	1,000	200	0.040	88%	0.04

To assess the effectiveness of the LSTM-GOA model in prioritising the scheduling of critical resources, experiments are conducted across multiple emergency scenarios, each incorporating different types of critical resources (e.g., emergency medical equipment, rescue personnel, fire trucks). In these scenarios, the urgency and prioritisation of resource allocation vary. The focus is on ensuring the timely allocation of critical resources during emergencies while maintaining overall scheduling fairness and efficiency.

The following key parameters are set for the different emergency scenarios:

1 Critical resource priority: Distinct priority levels are assigned to various types of critical resources. For instance, emergency medical equipment is given higher priority than rescue personnel, and rescue personnel are prioritised over fire trucks.

2 Emergency severity: Various emergency scenarios, including natural disasters and public health crises, are simulated, each with differing levels of resource scarcity.

3 Fairness and efficiency trade-off: The LSTM-GOA model's performance in prioritising critical resource scheduling is tested under varying weights for fairness and efficiency.

The results of the critical resource prioritisation experiments are presented in Table 7.

Table 7 Results of the critical resource prioritisation experiment

Scenario type	*Critical resource priority*	*Number of scheduling nodes*	*Response time (seconds)*	*MSE*	*Resource allocation fairness (weighted fairness)*	*Critical resource allocation accuracy (%)*	*Public resource allocation accuracy (%)*
Natural disaster	High (medical equipment), medium (rescue personnel), low (fire trucks)	500	200	0.045	85%	92%	80%
Disease control	High (medical equipment), low (rescue personnel), low (fire trucks)	600	210	0.038	88%	95%	76%
Fire emergency	High (fire trucks), medium (rescue personnel), low (medical equipment)	400	180	0.042	82%	90%	84%
Large-scale terrorism	High (medical equipment, fire trucks), medium (rescue personnel)	700	250	0.050	80%	94%	78%

According to Table 7, the LSTM-GOA model consistently prioritises the scheduling of critical resources, including medical equipment, rescue personnel, and fire trucks, across all scenarios. In the natural disaster scenario, for example, medical equipment is allocated the highest priority, followed by rescue personnel, with fire trucks receiving the lowest priority. The model schedules resources according to these priorities, ensuring the prompt allocation of critical resources. The critical resource allocation accuracy is generally high, reflecting the model's effectiveness in ensuring the rational distribution of critical resources during emergencies. In the natural disaster scenario, critical resource allocation accuracy reaches 92%, while in the large-scale terrorism scenario, it improves to 94%. Across various scenarios, the model maintains a high level of resource allocation fairness while also ensuring efficiency. Even in scenarios involving higher resource scarcity, such as natural disasters, the model successfully upholds fairness, particularly in the allocation of critical resources like medical equipment and rescue personnel. This ensures the rationality of resource distribution. The fairness of resource allocation fluctuates slightly across scenarios, generally being higher in less severe emergencies, such as disease control and fire emergencies. As the complexity of the scenario increases (e.g., in large-scale terrorism), the model's response time increases slightly. However, the prioritisation of critical resource allocation remains adequately ensured. Response time is a crucial metric in emergency scheduling. The LSTM-GOA model demonstrates the ability to respond rapidly in emergency situations. While response time is longer in high-intensity scenarios, such as large-scale terrorism, this is attributable to the increased resource scarcity and the greater complexity of the scheduling task. Nevertheless, the model continues to ensure the timely allocation of critical resources. Overall, the response time and mean squared error (MSE) values confirm that the LSTM-GOA model delivers strong scheduling performance, even in high-intensity emergency scenarios, offering both rapid responses and accurate scheduling solutions.

In this study, the GOA is employed for hyperparameter tuning, with the goal of optimising the performance of the LSTM model in emergency scheduling tasks. The hyperparameters optimised in this study include:

1 The number of hidden layers and units in the LSTM model, which determine its capacity and learning ability.

2 The population size, mutation probability, and crossover probability in GOA, which directly influence the global search capability of the algorithm, thereby affecting the optimisation of hyperparameters.

To align with the overarching problem framework, GOA is used to simultaneously tune both the LSTM model's hyperparameters and relevant parameters of the scheduling system, such as priority settings and resource allocation strategies. Depending on the characteristics of different emergency scenarios, GOA adjusts the corresponding hyperparameters to achieve optimal scheduling performance.

To assess the impact of hyperparameter tuning across various emergency scenarios, several experimental sets are conducted. These experiments involve adjusting the population size, crossover probability, and mutation probability of GOA, testing them in different emergency scenarios to observe how hyperparameter variations affected the scheduling performance of the LSTM-GOA model. Four typical emergency scenarios are selected: natural disasters, disease control, sudden fires, and large-scale terrorism. The tested parameters include population sizes (50, 100, 200), crossover probabilities (0.6, 0.7, 0.8), and mutation probabilities (0.05, 0.1, 0.15). The results of the hyperparameter tuning experiments are summarised in Table 8.

As shown in Table 8, in high-urgency scenarios, such as natural disasters and large-scale terrorism, larger GOA populations (e.g., 200) generally lead to faster scheduling response times. However, excessively large populations may result in slower algorithm convergence. To strike a balance between response time and computational complexity, a moderate population size (100) is selected. The adjustment of hyperparameters also directly influences the MSE. For instance, in the disease control scenario, a higher crossover probability (0.8) coupled with a moderate mutation probability leads to the optimal MSE value of 0.038, indicating the best performance. The tuned hyperparameters significantly enhance resource allocation fairness and the accuracy of critical resource allocation. In all scenarios, the model with optimised hyperparameters demonstrates high levels of resource allocation fairness and precise critical resource allocation. This is especially evident in the disease control and natural disaster scenarios, where both fairness and accuracy reached notably high levels. These results underscore the effectiveness of hyperparameter optimisation in enhancing the performance of the scheduling system, particularly in high-urgency situations.

Table 8 Hyperparameter tuning experiment results

Scenario type	*GOA population size*	*Crossover probability*	*Mutation probability*	*Scheduling response time (seconds)*	*MSE*	*Resource allocation fairness (weighted fairness)*	*Critical resource allocation accuracy (%)*
Natural disaster	50	0.7	0.1	220	0.045	85%	90%
Disease control	100	0.8	0.15	210	0.038	88%	93%
Sudden fire	200	0.6	0.05	180	0.042	80%	85%
Large-scale terrorism	100	0.7	0.1	250	0.050	82%	89%

4.5 Discussion

In this study, the LSTM-GOA model has shown remarkable advantages in resource scheduling in response to emergencies. Compared with traditional rule methods and other advanced algorithms, it has achieved higher prediction accuracy, scheduling efficiency and improved response time. Compared with previous studies, this study combines the time series prediction ability of LSTM neural network with the global optimisation characteristics of GOA, thus avoiding the limitations of a single algorithm. For example, the emergency dispatching method based on reinforcement learning proposed by Wang et al. (2023a) has excellent performance in some scenarios, but it lacks the ability to flexibly respond to sudden demand fluctuations, and the calculation cost is high; However, the LSTM-GOA model in this study shows strong robustness in complex environment. Especially in medical and transportation resource scheduling, the response time is greatly reduced (such as the response time is reduced by 47.2%). In addition, similar to PSO used by Zhang et al. (2022), this study also applies the optimisation algorithm, but the introduction of GOA made the hyperparameter optimisation more efficient, and the scheduling results improve in fairness and resource utilisation. Finally, Supreeth and Patil (2022) put forward a scheduling model based on GA optimisation, which can effectively solve some scheduling problems, but GA algorithm was easy to fall into local optimal solution, resulting in low scheduling efficiency and fairness. In contrast, the LSTM-GOA model not only improves the ability of global search by introducing GOA, but also obtains significant advantages in fairness and balance of resource allocation. The experimental results show that the LSTM-GOA model is superior to traditional methods and other optimisation algorithms in fairness and efficiency of resource scheduling.

5 Conclusions

5.1 Research contribution

The main contribution of this study is to propose an intelligent scheduling optimisation model based on the combination of LSTM and GOA to deal with the scheduling problem of urban public services under emergencies. Through in-depth analysis of the time series characteristics of urban public service resource demand and the impact of emergencies, this study designs an effective scheduling strategy, which significantly improves the prediction accuracy and scheduling efficiency of medical, transportation and energy resources. Compared with the traditional rule method, the LSTM-GOA model shows advantages in response time, fairness of resource allocation and scheduling efficiency. Introducing GOA to optimise the hyperparameter of LSTM model not only overcomes the local optimisation problem of traditional LSTM, but also improves the adaptability and robustness of scheduling system in complex environment, and fills the gap in resource scheduling optimisation in existing research.

5.2 Future works and research limitations

Although the proposed LSTM-GOA model performs well in emergency resource scheduling, it still has some limitations. Firstly, the computational efficiency and real-time performance of the current model in dealing with extreme emergencies or large-scale high-dimensional data still need to be further improved. To enhance the practical applicability of the LSTM-GOA model in emergency management systems, several key steps should be considered for future research. First, integrating the model with existing emergency management platforms is essential. Many current systems already feature resource scheduling and emergency response mechanisms. Therefore, efforts should focus on ensuring seamless interoperability between the LSTM-GOA model and these platforms. This can be achieved through API interfaces or modular design, enabling the model to support decision-making processes in scheduling while working in coordination with existing infrastructure. Additionally, conducting small-scale field tests and case studies will be vital to validate the model's effectiveness in real-world settings. Typical emergency scenarios, such as large-scale fires or sudden epidemics, should be selected for localised tests to evaluate the model's performance. These tests will provide valuable insights into the model's adaptability, flexibility, and scheduling efficacy, facilitating further adjustments and optimisation based on real-world feedback. Considering the significant variation in emergency management needs across cities and regions, cross-regional collaboration and promotion are also essential. During the promotion process, the model should be customised to meet the specific needs of different cities, ensuring stability and accuracy across varying scales and types of emergency events. Future research could explore methods for adapting the model to diverse regional requirements through cross-regional collaborations and experiments. Several key areas should be prioritised in future research. First, conducting field trials in multiple emergency scenarios is necessary to ensure the model's stable and effective operation during actual emergencies. Second, investigating real-time updates and the model's adaptability is crucial, particularly in dynamic emergency situations where the model must adjust scheduling decisions based on newly received data. Moreover, data privacy and security concerns must be addressed, especially when dealing with public resource scheduling and emergency management systems. Ensuring the protection of data and user privacy is of paramount importance. Lastly, conducting case studies across various cities and regions will provide valuable insights into the model's performance in diverse environments. This will contribute to enhancing the model's generalisability and applicability, ensuring its effective deployment in a wide range of emergency scenarios.

Funding

This work was supported by Doctoral Research Startup Fund Project of Nantong Institute of Technology (Grant No. 2025XKB29), Jiangsu Province Higher Education Informatisation Research Major Project (Grant No. 2025JSETKT036), Nantong Institute of Technology Artificial Intelligence General Education Teaching Reform Research Special Project (Grant No. 2025JJG005), and Nantong Institute of Technology Higher Education Teaching Reform Research Project (Grant No. 2025JJG042).

Declarations

All authors declare that they have no conflicts of interest.

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