APEM journal
Advances in Production Engineering & Management
Volume 20 | Number 2 | June 2025 | pp 254–276
https://doi.org/10.14743/apem2025.2.539
ISSN 1854-6250
Journal home: apem-journal.org
Original scientific paper

Optimizing emergency home healthcare scheduling with improved Quantum-behaved Particle Swarm Optimization

Zhang, H.K.[a,*], Yang, S.[a], Zheng, Q.M.[a], Liang, H.R.[b]

[a]Business School, Beijing Technology and Business University, Beijing 100048, P.R. China
[b]China Culture Administration Association, Beijing 100013, P.R. China

A B S T R A C T

With the intensification of China's aging society, improving the health management and emergency response capabilities of the elderly at home has become an urgent issue that needs to be addressed. To meet this challenge, an Emergency Home Monitoring System (EHMS) that utilizes real-time data and wearable device monitoring is developed to optimize the Emergency Medical Transport Vehicle and Hospital Scheduling Problem (EMTVHSP) for elderly people at home. The patient's condition classification and waiting time are effectively combined to establish an Emergency Medical Transport Vehicle and Hospital Scheduling Model (EMTVHSM). Specifically, the optimization objective of the model is to minimize the maximum rescue time, thereby improving the allocation efficiency of medical resources and the efficiency of patient transfer. To solve this model, an Improved Quantum-behaved Particle Swarm Optimization (IQPSO) is proposed. The algorithm significantly improves the ability to solve complex scheduling problems by introducing neighborhood structure, improving constraint processing, introducing mutation operations and designing innovative resource reallocation strategies. Simulation results show that the dynamic resource scheduling method based on the IQPSO has significant advantages over traditional algorithms in reducing the maximum patient transfer time and improving scheduling efficiency and the optimization effect is improved by an average of 6.1 %. The emergency home monitoring system, scheduling model, and optimization algorithm designed effectively provide a more efficient emergency medical resource scheduling solution for elderly people at home and offer strong technical support and a practical basis for addressing health management challenges in an aging society.

A R T I C L E I N F O

Keywords:
Emergency home monitoring system;
Emergency medical resource scheduling;
Treatment priority;
Quantum-behaved Particle Swarm Optimization;
Cellular neighbor network;
Roulette wheel selection;
Machine learning

**Corresponding author:*
zhanghankun@btbu.edu.cn
(Zhang, H.K.)

Article history:
Received 26 January 2025
Revised 29 May 2025
Accepted 7 June 2025

1. Introduction

In China, the issue of population aging is becoming increasingly prominent, with the proportion of people aged 65 and above continuing to rise, driving an urgent need for an emergency home health management system [1]. To address this challenge, we propose an Emergency Home Monitoring System (EHMS). This system aims to monitor the health status of elderly individuals in real-time and respond rapidly in case of emergencies [2]. Through the integration of smart devices and monitoring platforms, the system consolidates medical resources, social service resources and transportation resources to ensure efficient allocation during health crises. By dynamically optimizing resource allocation, the system enhances overall response speed and service availability, providing comprehensive health protection for the elderly.

Emergency health services face challenges ranging from limited resources available to increased demand for a variety of reasons, such as population ageing, more transport and increasingly urbanized areas [3]. In addition, larger-scale emergencies that lead to more affected individuals require that emergency organizations make more extensive use of their resources. In recent years, the number of emergencies worldwide has been increasing. In particular, with the aging of society, home healthcare has become a growing concern. This makes emergency resource scheduling an important aspect of emergency response [4]. Many affected countries have different experiences in responding to small-scale emergencies; the present study explores emergency resource mobilization management in this context. Existing emergency medical rescue systems have many shortcomings in resource scheduling and response speed, especially when it comes to the special needs of homebound elderly individuals, making it difficult to provide a quick and effective response [5]. Therefore, constructing an intelligent system capable of real-time monitoring, rapid response and scheduling based on changes in the elderly's health conditions is key to improving the effectiveness of emergency rescue for the elderly at home.

To address the challenges of emergency healthcare for homebound elderly individuals, an innovative emergency home health management system that leverages real-time data and wearable device monitoring is proposed. Wearable devices continuously gather essential health data, including heart rate, blood pressure, and oxygen saturation, while also monitoring the patient's physical activity and movement behaviors. These devices offer real-time health insights, allowing healthcare professionals to remotely track elderly individuals at home, identify early warning signs of potential emergencies, and initiate prompt interventions. The system features dynamic monitoring and rapid response mechanisms and integrates a dynamic resource scheduling model that considers not only the fairness of patient rescue, but also location, traffic conditions, and available transportation resources [6]. This model ensures that medical resources are allocated efficiently, minimizing the patient transfer time and optimizing the overall response time. When home health problems occur, they often result in casualties, which requires the design of an effective humanitarian medical relief programmer. The reliable humanitarian medical network and the distribution of patients are the important contents of the medical rescue plan, which directly affects the rescue efficiency [7]. Therefore, design a humanitarian medical relief network, the distribution of patients to medical institutions.

The Quantum-behaved Particle Swarm Optimization (QPSO) is an enhanced version of the traditional Particle Swarm Optimization (PSO), designed to improve search efficiency and solution quality in optimization problems [8]. Unlike the standard PSO, which relies on particles moving in a fixed search space, QPSO introduces quantum mechanical principles to model the behavior of particles. This allows particles to explore the search space in a more flexible and probabilistic manner, increasing the likelihood of escaping local optima and improving the global search capability. The QPSO has demonstrated significant advantages in solving complex optimization problems, particularly those involving dynamic and nonlinear objective functions, such as resource scheduling in emergency healthcare. In the context of emergency medical resource scheduling [9], the QPSO offers several key advantages. It efficiently handles the complexity and dynamics of the scheduling problem, where multiple factors, such as patient condition classification, waiting times and transportation logistics, must be considered. The probabilistic nature of the algorithm allows it to explore a wider solution space, making it capable of finding optimal or nearly optimal solutions, even in highly complex and constrained environments. However, the traditional QPSO still faces challenges, such as premature convergence and inefficient handling of constraints, particularly in real-time, dynamic resource allocation scenarios. To address these limitations, an improved version of the QPSO, termed the Improved Quantum-behaved Particle Swarm Optimization (IQPSO), is introduced. The IQPSO enhances the traditional QPSO by incorporating several key improvements, such as strengthening the global search ability, introducing a more effective constraint handling mechanism and incorporating a mutation operation to increase solution diversity and prevent premature convergence. These modifications make the IQPSO more robust and capable of solving the dynamic and complex resource scheduling problem encountered in emergency healthcare situations. Simulation results show that the IQPSO outperforms traditional QPSO and other standard algorithms in terms of reducing patient transfer time and improving scheduling efficiency, demonstrating its effectiveness in real-time emergency medical resource scheduling.

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 discusses the methodology adopted in this research. Section 4 presents the mathematical model, including the problem description, assumptions and formulation. Section 5 introduces the metaheuristic approach, detailing the Quantum-behaved Particle Swarm Optimization (QPSO) and its improved version with specific components such as cellular neighbor networks, constraint handling, mutation operators and the roulette wheel selection strategy. Section 6 provides a case study, covering the case description, experimental design, parameter settings and results. Section 7 offers a discussion of the findings. Finally, Section 8 concludes the study and outlines directions for future work.

2. Literature review

In this section, we first review the development of emergency management systems. Next, we introduce the dynamic resource scheduling problem for rescue vehicles and hospitals, along with the corresponding models, focusing on how to optimize the allocation of emergency resources to improve response efficiency.

The emergency management system has evolved from simple emergency responses to a modern, comprehensive management approach. With respect to emergency medical service systems, developed a web-based emergency management system that integrates geospatial information and technology, Global Positioning System and optimization technologies, we designed a system consisting of two subsystems, emergency reporting and ambulance routing [10]. The aim was to develop a tool for assessment of the pre-hospital EMS system using the World Health Organization (WHO) health system framework. The resultant information is expected to provide a holistic picture of the pre-hospital emergency medical services and develop key recommendations for PEMS systems strengthening [11]. Transforming the system into a unified system of high-quality emergency care for all patients, improving overall public health through harm control and disease prevention programmers and engaging in disease surveillance as a full partner and being prepared to meet all types of new community needs [12]. The aim is to design a robust two-layer EMS system, while considering the requirements of inherent uncertainties. A two-stage stochastic programming location assignment model is proposed to determine the location of the ambulance station, the number and type of ambulances and the service area of each ambulance station [13] Through the integration of medical information system and information communication technology, an emergency support system based on WiMAX is proposed, to meet the needs of the public for convenient, fast, safe, people-centered emergency support operation. The system consists of a medical service center, an Emergency Medical Service hospital and an emergency ambulance [14]. The study established a model for emergency material preparation and scheduling based on queueing theory and further established a workflow system for emergency material preparation, scheduling and transportation based on a Petri net, resulting in a highly efficient emergency material preparation and scheduling simulation system framework [15]. This article evaluates and presents the *Architectural blueprint* for disaster management research at a macro level, mapping the research into five attributes of a disaster and cross-listing the data for these five parameters, for a deeper understanding of disaster research [4]. The study proposes a 15-dimensional framework for analyzing new forms of collaboration. The framework is applied to the field of information system by using the theory of social technology system and participatory design method [3]. A two-stage stochastic programming model was proposed to determine how to locate two types of ambulances in the first stage and solution priority emergency patients in the second stage after the call arrival scenario was made public. Demonstrates how the basic model adapts to include non-transport vehicles. A model formula is extended to the basic model to consider the probabilistic travel time and the general utility scheduling of ambulance priority to patients [16]. A disaster response and recovery decision support system based on hybrid meta-heuristic is proposed [17].

In the aspect of emergency medical rescue vehicles and hospital scheduling, it usually needs a lot of emergency materials and personnel scheduling when dealing with various disasters and other public events, emergency medical resource scheduling plays a key role. A multi-objective optimization model for urban logistics distribution networks (ULDN) has been proposed, aiming to minimize vehicle usage, transportation costs, penalties for missed time windows, carbon emissions, and accounting for urban traffic congestion impacts on total costs [18]. A multi-objective optimization model for dynamic manufacturing resource allocation is explored, with an improved NSGA-II algorithm proposed to address this issue. The study demonstrates that the algorithm significantly enhances population diversity and global search capability, effectively providing efficient and reliable resource allocation solutions in dynamic manufacturing environments [19]. The genetic algorithms (GA) were employed to determine the precise forms of the polynomial, and the developed models are crucial for quantifying the impact of individual input parameters, thereby enhancing our understanding of key system components in the literature [20]. According to the needs and characteristics of patients, different groups of patients are defined, and a mixed integer linear programming model is proposed to find out the optimal route order of each ambulance and to minimize the recent service completion time (SCT) and the number of patients whose conditions deteriorate due to untimely medical services [21]. A multi-period online decision-making problem is focused on, simulating the process of information acquisition and providing a reference for how previous decisions affect future logistics plans in the emergency resource scheduling scenario [22]. In order to quantitatively describe the problem of minimizing rescue time in emergency logistics, a rescue resource allocation solution for storm surge submerged logistics was proposed. A mixed integer linear programming (MILP) method is proposed to verify and compare the optimal performance of emergency logistics scheduling model. Improve efficiency in creating quality quotas [23]. By building and studying Markoff's decision-making process model to determine which types of ambulances (servers) are sent to patients in real time, these problems are solved. The basic model considers the loss system in finite time interval and gives the deformation model of infinite time interval and mean return criterion [24]. A patient transportation and distribution model considering ambulance routing and hospital operating conditions is proposed. The model consists of a cell transport model and a nonlinear therapeutic impedance function. The Joseph-Louis Lagrange heuristic method is used to decompose the problem into two relatively easy sub-problems to speed up the modelling [25]. It is suggested that the medical supplies scheduling method should be adopted in major public health emergencies, and a rapid and accurate medical supplies solution should be formulated, this includes the distribution of medical supplies per vehicle to hospitals and the distribution of supply orders per vehicle to hospitals [26]. An optimization-based integrated decision-making model was developed to assist health-care decision makers in planning ambulances immediately and efficiently to relocate critically ill patients from their places of residence [27]. An emergency resource scheduling model with stochastic resource demand and unreliable transportation channel is established. There is also a reliable but more expensive transportation channel. The basic model of expected total cost optimization is established, which ignores the constraint of reliable channel capacity and the demand satisfaction rate [28]. The single-objective model aims at the shortest scheduling time of emergency resources, and the multi-objective model aims at the shortest scheduling time of emergency resources and the shortest number of emergency rescue bases, using operational research voting Analytic hierarchy process to solve the model [29]. A post-disaster emergency vehicle scheduling and routing optimization method based on data fusion support is studied. A scheduling and routing simulation model is developed, and a case study is conducted to evaluate the performance of the proposed approach [30]. A hybrid intelligent algorithm is proposed for modeling and solving the Job Shop Scheduling Problem (JSSP), in which a multiple-refined random generation is employed, and the advantages of genetic algorithms, particle swarm optimization, and simulated annealing are integrated to enhance solution accuracy [31]. Two models are established, considering the differences between the same and varying degrees of injury, in which the relative cost of deprivation is one of the decision-making objectives emphasizing equity, the duration of halfway tolerable pain serves as a time window constraint to highlight rescue priorities. After proving the NP difficulty of the model, a new heuristic based on ant colony optimization is designed, which improves the convergence speed of the algorithm [32]. An improved ant colony algorithm is proposed and modeled to solve the multi-resource allocation problem in cloud computing for the new energy industry, aiming to optimize task response time and achieve load balancing under system constraints [33]. A multi-objective resource allocation model considering both efficiency and fairness is proposed. The objective of the model is to minimize the total allocation cost of resources and the total loss caused by insufficient resources. And Particle swarm optimization the model [34]. A new disaster responder routing and scheduling (DRPRS) model is proposed, which has efficiency, fairness and risk objectives and is subject to work and rest-related constraints [35]. A seven-dimensional QoS model for distributed computing resources in the Internet of Vehicles is transformed into two key priorities, and a dynamic greedy algorithm is proposed for task scheduling based on weighted graph models [36]. Three new mathematical formulas are proposed, which differ in the way they establish scheduling decision and crew synchronization and develop effective inequalities based on some special properties of the problem [37]. A new mixed integer linear programming (MILP) model is proposed to minimize the rescue/job completion time for all accidents by optimizing the allocation and scheduling of non-expendable resources [38]. The rescue unit allocation and scheduling problem (RUASP) with fuzzy processing times is addressed through an evolutionary approach. A steady-state grouping genetic algorithm (SSGGA) approach is presented to minimize the total weighted completion time of the incidents, where the weights correspond to the severity levels of the incidents [39].

Based on the discussion above, the main contributions of this paper are as follows:

- We have proposed an EHMS for home-based elderly care, which integrates monitoring devices such as smart bracelets and realizes real-time upload of dynamic data.
- The core of this system lies in the construction of an EMTVHSM, which fully considers the classification of patients' conditions and waiting times to comprehensively measure and evaluate the actual effectiveness of rescue operations.
- To address the aforementioned issues, we have designed an IQPSO. The main improvements of this algorithm include the introduction of a neighborhood structure, optimization of constraint handling methods, and the incorporation of mutation operations, which significantly enhances its ability to solve complex scheduling problems.

3. Methodology

In response to the increasingly severe challenges of an aging society, it is particularly important to build an Emergency Home Monitoring System (EHMS). With the increase in the elderly population, it is necessary to strengthen the health management and emergency response capabilities of the elderly at home to ensure their life safety and health. The construction of the home emergency monitoring system aims to effectively improve the efficiency of emergency rescue for the elderly at home through real-time monitoring, precise scheduling and rapid response. The system mainly consists of three modules: monitoring center module, information transmission module and emergency medical resource scheduling module. The emergency home management system is shown in Fig. 1.

The diagram illustrates the overall architecture of the EHMS, with a government-led monitoring center at its core. Home health monitoring using artificial intelligence technology, along with big data, 5G, AI and cloud computing, can identify the physiological patterns and behavior habits of the elderly, enabling more accurate health predictions. The monitoring center receives real-time data uploaded from patient monitoring devices and sends data requests to hospitals and emergency vehicles while also receiving feedback from these entities. All collected data, including the patient's basic information (such as name, age, blood pressure, heart rate, location, etc.), the number and locations of hospitals, as well as the availability, number and locations of vehicles, are integrated and transmitted to the scheduling model. Based on this data, an emergency medical transport vehicle and hospital scheduling model is constructed and solved using the IQPSO. The final scheduling solution is generated to ensure efficient emergency response and resource allocation.

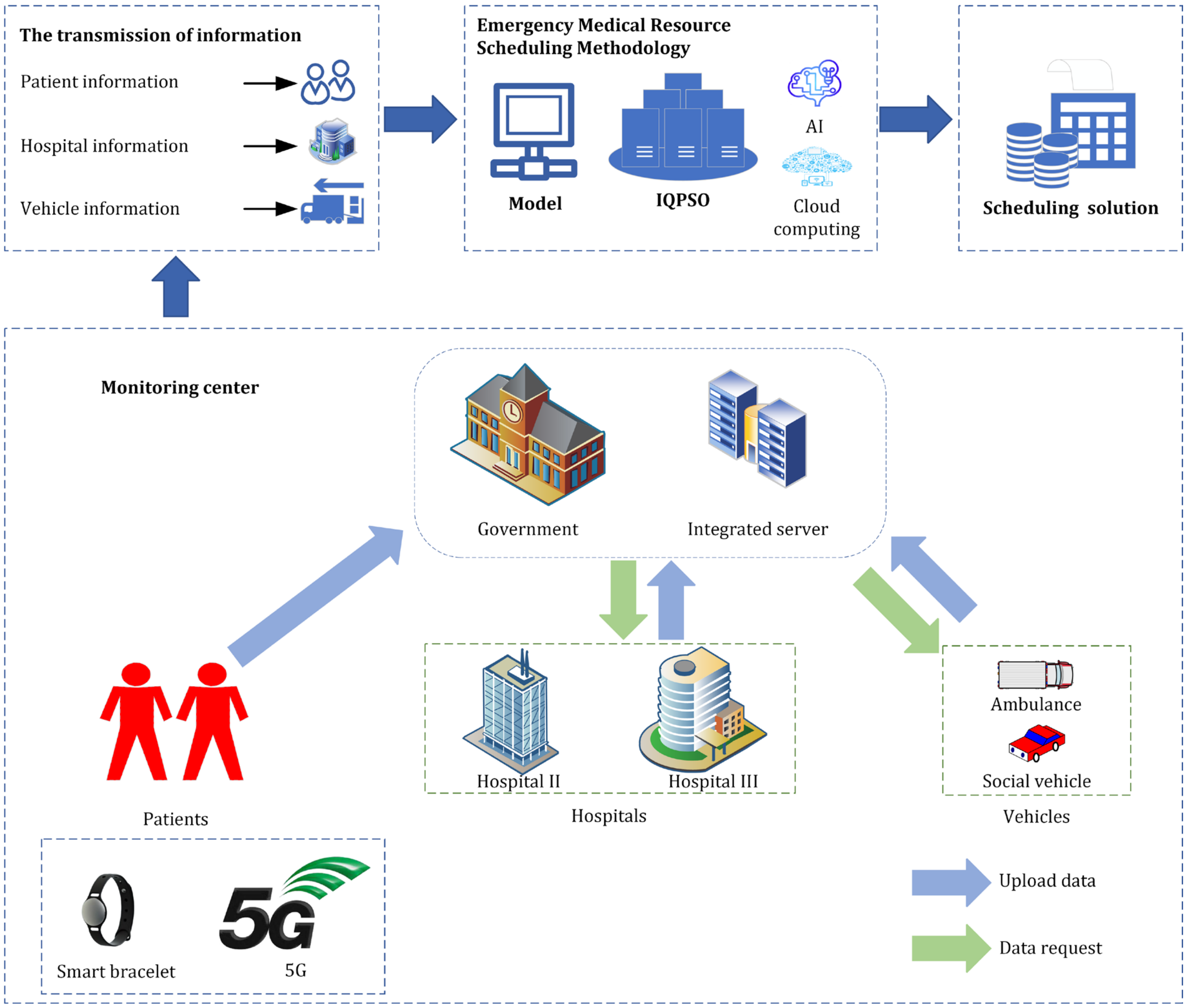

Fig. 1 The Emergency Home Management System

4. Mathematical model

Our research differs from the existing literature in that it applies artificial intelligence technology to home health intelligence monitoring. The main focus is on the core medical resources of ambulances and hospitals, with the objective of minimizing transit time. The literature referenced in this paper primarily addresses casualty scheduling in densely populated areas, providing valuable insights but leaving room for further exploration and innovation in the field of home health intelligence monitoring.

4.1 Problem description

The dynamic scheduling problem of medical emergency support resources is closely related to the pain degree and survival probability of patients. Effective logistics operations can greatly reduce the extent of damage. The paper looked at rescue vehicles and core resources for hospital care. Rescue vehicles, including ambulances and social vehicles, are responsible for transporting the wounded from their homes to hospitals. Social vehicles mainly consider taxis that can be arranged for the system or ride-hailing, rather than private vehicles. Hospitals are mainly divided into second-level hospitals and third-level hospitals. Patients are classified into three levels based on severity, Level I for the most critical, Level II for moderately severe and Level III for the least severe. The i, j and k are used to represent the number of patients, vehicles and hospitals, respectively. The emergency medical transport vehicle and hospital scheduling problem is shown in Fig. 2.

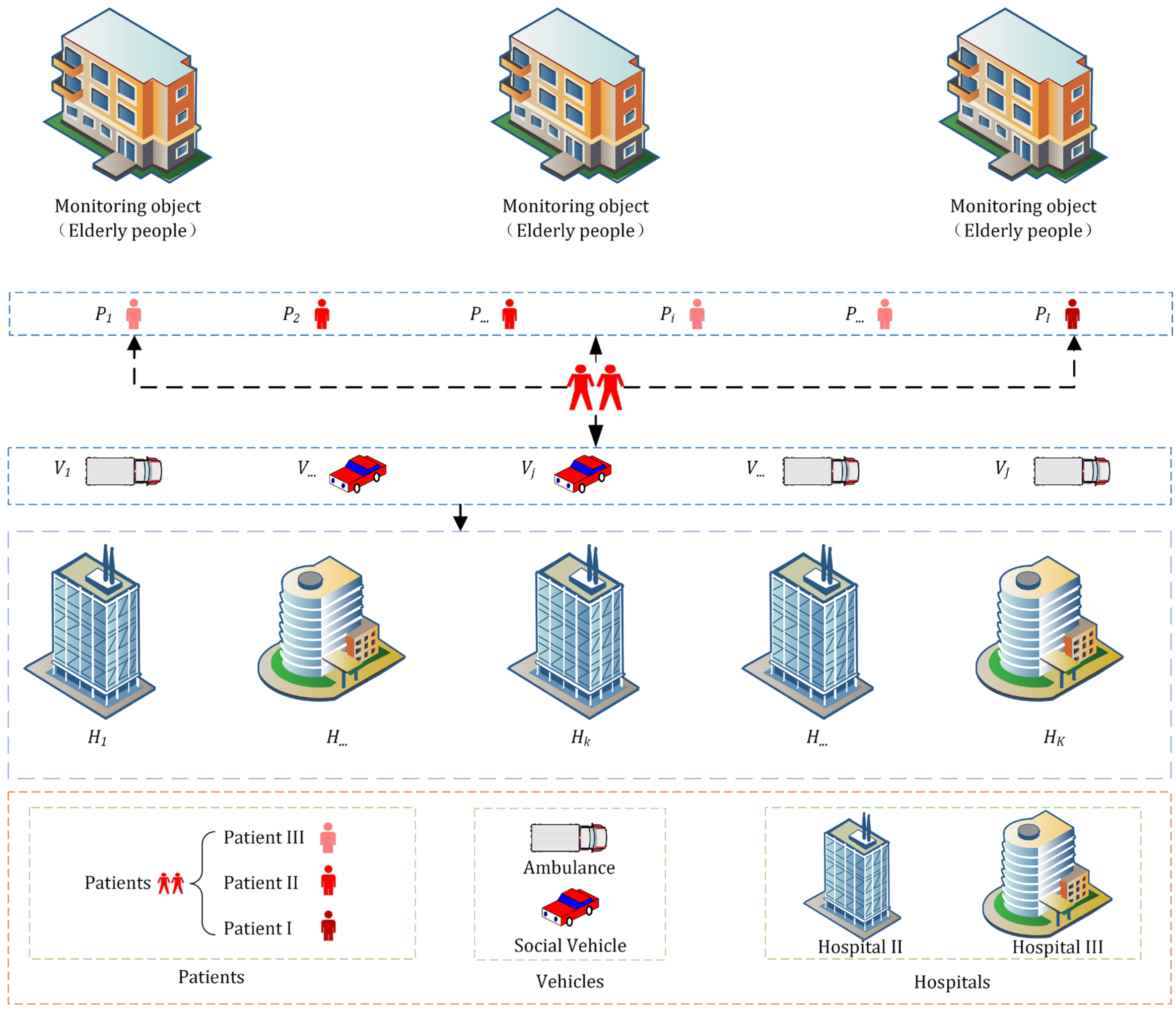

Fig. 2 The Emergency Medical Transport Vehicle and Hospital Scheduling Problem

4.2 Assumptions

As mentioned earlier, several uncertainties influence the outcome of scheduling home-to-hospital patient transfers. In this work, we focus on the decision-making process for scheduling patients to the hospital by ambulance. The specific assumptions are as follows:

- Patient location and severity are obtained through satellite technology and intelligent monitoring systems.
- Patients are categorized by injury severity and vital signs and transported to suitable hospitals.
- Each vehicle transports one patient at a time, and simultaneous responses involves a single interview per patient.
- The time from patients' homes to vehicles is negligible.
- Routes between hospitals and patients' homes are feasible, with stable traffic conditions.
- Urban climate, major natural disasters and public health emergencies are stable.
- Patients receive prompt medical care upon arrival at the hospital.

4.3 Formulation framework

A specific Emergency Medical Transport Vehicle and Hospital Scheduling Model (EMTVHSM) is given, where P denotes the patients that need to be transported to the hospital, where $P = P_I \cup P_{II} \cup P_{III}$ indicates that the patients transported to the hospital are divided into three grades with different weights. That is, P_I, P_{II} and P_{III} represent the set of patients at the corresponding level, respectively. ω_i represents the weight of the i-th patient, $\omega_i = \{\omega_I, \omega_{II}, \omega_{III}\}$, $\omega_i \geq 1$, in this paper, ω_I is assigned a value of 1, ω_{II} a value of 2, and ω_{III} a value of 3. W_i represents the time of the i-th patient to wait for system allocation, A_j represents the availability time of the j-th vehicle, $d_{i,j}$ represents the distance from the location of vehicle j when it is available to the location of patient i, L_j represents the set of times of the j-th vehicle was actually used, $L_j = \{1,\cdots,N_j\}$, N_j represents the number of times of the j-th vehicle was actually used, v_j represents the velocity of the j-th vehicle. H denotes the set of hospitals, V represents the set of vehicles, T_i represents the time from the monitoring system reports that the patient needs to be sent to the hospital to the patient arrives at the hospital. $t_{j,l-1}$ represents the time when the vehicle j takes the previous patient to the hospital, where $l-1$ represents the previous time of the l-th transhipment of a specific vehicle. $d_{l-1,i}$ represents the distance between the location where the vehicle dropped off the previous patient and patient i. Finally, we have the decision variables:

$$x_{i,j,l,k} = \begin{cases} 1, & \text{Patient } i \text{ is transported to hospital } k \text{ by vehicle } j \text{ for the } l\text{-th time} \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

The optimization problem is formulated as:

$$f = \min max\{T_i\} \tag{2}$$

$$T_i = \begin{cases} \sum_{j\epsilon V}\sum_{l\epsilon L_j}\sum_{k\epsilon H} x_{i,j,l,k}\left(e^{\frac{W_i+A_j+\frac{d_{i,j}}{v_j}}{\omega_i}}\left(W_i + A_j + \frac{d_{i,j}}{v_j}\right) + \frac{d_{i,k}}{v_j}\right), l = 1 \\ \sum_{j\epsilon V}\sum_{l\epsilon L_j}\sum_{k\epsilon H} x_{i,j,l,k}\left(e^{\frac{W_i+t_{j,l-1}+\frac{d_{l-1,i}}{v_j}}{\omega_i}}\left(W_i + t_{j,l-1} + \frac{d_{l-1,i}}{v_j}\right) + \frac{d_{i,k}}{v_j}\right), l \geq 2 \end{cases} \tag{3}$$

$$\sum_{j\in V}\sum_{l\epsilon L_j}\sum_{k\epsilon H} x_{i,j,l,k} = 1, \forall i \in P \tag{4}$$

$$\sum_{j\in V}\sum_{l\epsilon L_j} x_{i,j,l,k} = 1, \forall i \in P \tag{5}$$

$$\sum_{k\epsilon H} x_{i,j,l,k} = 1, \forall i \in P \tag{6}$$

$$\sum_{i\in P} x_{i,j,l,k} = 1, \forall j \in V, \forall l\epsilon L_j \tag{7}$$

Eq. 2 is the objective function to minimize the maximum value of T_i for all patients. Eqs. 4-7 are constraints. Eq. 4 means that each patient must be assigned exactly once. Eq. 5 means that each patient must be assigned the specific time of unique vehicle only once. Eq. 6 means that each patient must be assigned to a unique hospital. Eq. 7 means that the specific time of each vehicle can transport only one patient.

5. Metaheuristic method

To address the resource scheduling problem in dynamic environments, a metaheuristic algorithm is adopted and improved to enhance its performance.

5.1 Quantum-behaved Particle Swarm Optimization

Inspired by the related work of Heppner and Grenander [40] and the social behavior of a flock of birds and a school of fish, Particle Swarm Optimization (PSO) was proposed in 1995, which is very popular in many fields [41]. To address the limitations of PSO, Quantum-behaved Particle Swarm Optimization (QPSO) was introduced to enhance PSO's exploration and exploitation capabilities within the solution space. This improvement is achieved by increasing the particle swarm's population diversity through the motion of quantum particles, each existing in a quantum superposition of two classical physical locations at any given moment [9]. The flow chart of the QPSO is shown in Fig. 3.

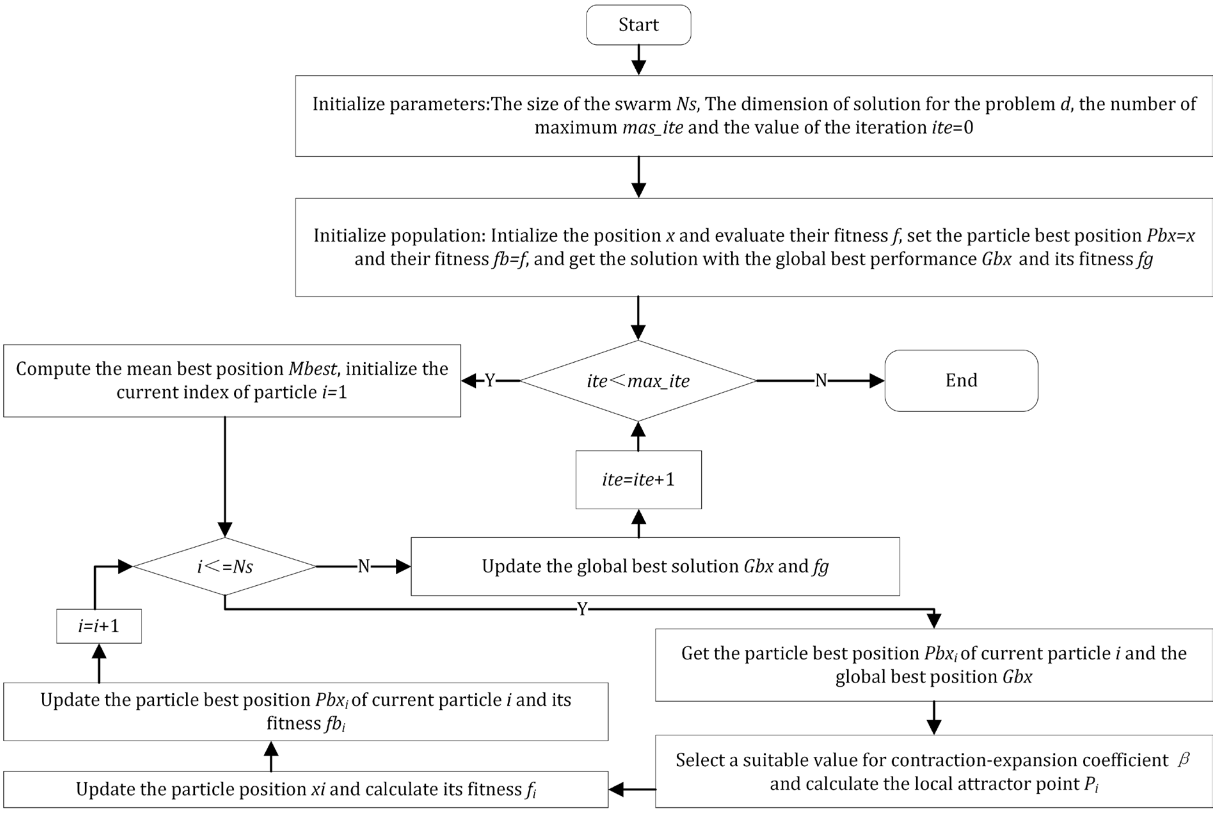

Fig. 3 The flow chart of QPSO

5.2 Improved Quantum-behaved Particle Swarm Optimization

The Improved Quantum-behaved Particle Swarm Optimization (IQPSO) enhances QPSO by introducing a small-world network structure for global optimization, utilizing three types of neighborhood networks, the Von Neumann neighborhood, the Moore neighborhood and the Extended Moore neighborhood. Constraints are handled by randomly adjusting out-of-bound dimensions with equal probabilities of selecting random values, personal best locations, global best locations, or boundary values. Additionally, a mutation operation is incorporated, where the mutation probability dynamically increases as iterations progress. This is achieved by introducing the number of times an individual has not improved and modifying the mutation coefficient to emphasize exploration in later iterations.

The algorithm also employs a random roulette-based mutation strategy for task reassignment. Patients with longer delivery times are prioritized for reassignment and vehicles with shorter delivery times are more likely to be selected for new assignments. This ensures an efficient balance between exploration and exploitation while maintaining diversity. The improved strategies effectively enhance the algorithm's ability to find optimal solutions under complex constraints. The general pseudo-code of the IQPSO is shown in Algorithm 1.

Algorithm 1 The general pseudo-code of the IQPSO

Step 0: Setting the parameters. $MaxIter$ is set, along with the swarm size N_s and the dimensionality of the problem N_d. The contraction-expansion coefficient $beta$ is defined, starting with a maximum value $beta\_max$ and gradually reducing to a minimum value $beta\_min$. Mutation parameters a and $delta$ are specified. Parameters for constructing the small-world network are set, including the number of rows r, columns c, rewiring probability p and network depth d. The number of nearest neighbors k is set. Finally, chaotic maps are initialized to facilitate random number generation.
Step 1: Generate the small-world network. Construct the network structure using the specified parameters. Obtain the nearest neighbors for each particle in the swarm.
Step 2: Initialization of the swarm. The swarm is initialized by randomly locations x to each particle within the solution space, with the random numbers generated using the Logistic map.
Step 3: Initialize the historical optimal location of each individual.
Step 4: Initialize the global best location.

Step 5: Initialize chaotic random numbers. Generate chaotic random sequences for parameters $k, u, theta$ and others required for dynamic updates.
Step 6: Iterative process.
for $ite = 1 : MaxIer$
Step 6.1: Update K nearest neighbors best.
Step 6.2: Generate chaotic random values for parameters k, u, and $theta$.
Step 6.3: Calculate the mean best location $Mbest$ and contraction-expansion factor $beta$.
Step 6.4: Update particle location.
Step 6.5: Handle boundary constraints for updated location.
Step 6.6: Perform mutation operations. If a particle is selected to perform the mutation operation, the roulette strategy is adopted.
Step 6.7: Evaluate the fitness of the individual.
Step 6.8: Update the personal best location Pb.
Step 6.9: Update the global best location Gb.
Step 6.10: Record the global best fitness.
Step 6.11: Update the continuous unimproved number of each particle.
end

Cellular neighbor network introduction

In human society or a network, cellular neighbor structures can achieve good performance [42]. Therefore, the cellular neighbor network proposed in the literature [42] is introduced into the IQPSO. In the IQPSO, a cellular neighborhood network is introduced to enhance the exploration and exploitation capabilities of particles. Each cell represents the current location of a particle, which corresponds to the best location it has found in the search space. The cellular neighborhood structure defines the information exchange among particles, influencing the algorithm's convergence performance and solution quality. Fig. 4 shows examples of cellular neighborhoods and cellular neighbor networks.

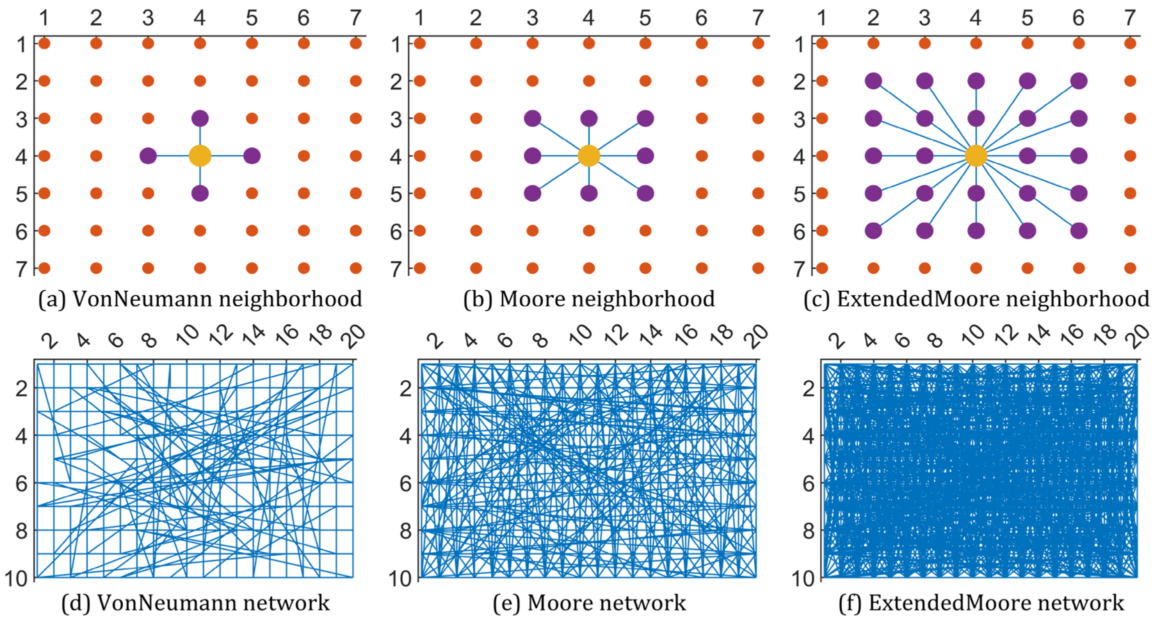

Fig. 4 The examples of cellular neighborhoods and cellular neighbor networks

The IQPSO adopts three classic neighborhood structures: the Von Neumann neighborhood, the Moore neighborhood and the Extended Moore neighborhood. Figs. 4a, 4b, and 4c show examples of these neighborhoods. In these subfigures, the orange squares represent the observed object and the purple squares represent its neighbors. Examples of their cellular neighbor networks are shown in subfigures Figs. 4d, 4e, and 4f.

Constraint handling

During the location update process in the IQPSO particles may violate the solution space boundaries. So, the particle location $x(i, j)$ is adjusted as follows.

$$x(i,j) = \begin{cases} lu(1,j) + \big(lu(2,j) - lu(1,j)\big) \cdot rand, & 0 \le ra_{repl} < 0.25 \\ Pbx(i,j), & 0.25 \le ra_{repl} < 0.5 \\ Gbx(i,j), & 0.5 \le ra_{repl} < 0.75 \\ lu(1,j), & x(i,j) < lu(1,j) \ \wedge \ ra_{repl} \ge 0.75 \\ lu(2,j), & x(i,j) > lu(2,j) \ \wedge \ ra_{repl} \ge 0.75 \end{cases} \tag{8}$$

In the equation, $lu(1,j)$ and $lu(2,j)$ represent the lower and upper boundaries of the j-th dimension, respectively. The variable $rand$ is a uniformly distributed random number within the interval $[0,1]$. $Pbx(i,j)$ and $Gbx(i,j)$ are the personal best and global best location s for the j-th dimension, respectively. The variable ra_{repl} is generated from a uniform distribution $U(0,1)$, determining the probability of selecting each update rule. This ensures that the updated location remains within the valid boundaries while utilizing individual and global knowledge for optimization.

Mutation operator

In order to enhance the diversity of the algorithm, the mutation operator is introduced [43]. However, IQPSO incorporates three key differences. First, Historical Non-Improvement Count: Mutation probability incorporates each individual's non-improvement count, calculated as $\exp\left(\frac{no\_diversities}{\delta}\right)$, increasing the mutation likelihood for stagnant particles. The variable $no\_diversities$ represents the number of iterations in which an individual has not improved. Second, Iteration-Dependent Mutation Probability: where mutation probability decreases over iterations ($e > s_{r_{rand}}$), IQPSO reverses this to increase mutation probability $\left(e < s_{r_{rand}}\right)$ as e decreases with iteration, enhance the later exploration. Third, Logistic Map for Random Numbers. IQPSO generates all random numbers. This includes the random numbers used in the mutation process. It uses the Logistic map to introduce chaotic randomness. This approach enhances diversity and improves the effectiveness of the search. If a particle meets the mutation condition, the roulette wheel selection strategy is executed.

Roulette wheel selection strategy

The roulette wheel selection strategy assigns probabilities to options based on their weights, ensuring higher chances for those with greater importance. The roulette wheel selection strategy in IQPSO first identifies the task with the longest service time (e.g., the most delayed patient). It then selects a new vehicle for reassignment by prioritizing vehicles with shorter workloads using an inverse weighted probability. Finally, the selected task is reassigned to the new vehicle, optimizing resource allocation and balancing workload. The roulette selection strategy description is shown in Fig. 5.

First, calculate the weighted time for each patient and the vehicle used for transportation. Second, identify the patient with the maximum weighted time and highlight it; for example, patient P6 is marked in yellow in the example. Then, identify all patients being transported by the same vehicle as the patient with the maximum weighted time (in this case, vehicle V3 transporting patients P2 and P6). Apply a roulette wheel selection strategy, where the weighted transportation time for each patient (P2 and P6) is used as the selection probability. Patients with longer transportation times have a higher likelihood of being selected. Select the patient who needs to switch vehicles, such as P6. Third, identify all vehicles other than the one transporting the patient with the maximum weighted time (P6), which in this case are vehicles V1 and V2. Apply a roulette wheel selection strategy, where the weighted time of the last patient transported by each of the other vehicles is used as the selection probability. Vehicles with longer transportation times will have a lower chance of being selected. Select a new vehicle to transport the patient (P6), such as V2. Fourth, mark the vehicle changes. Fifth, give the final scheduling solution.

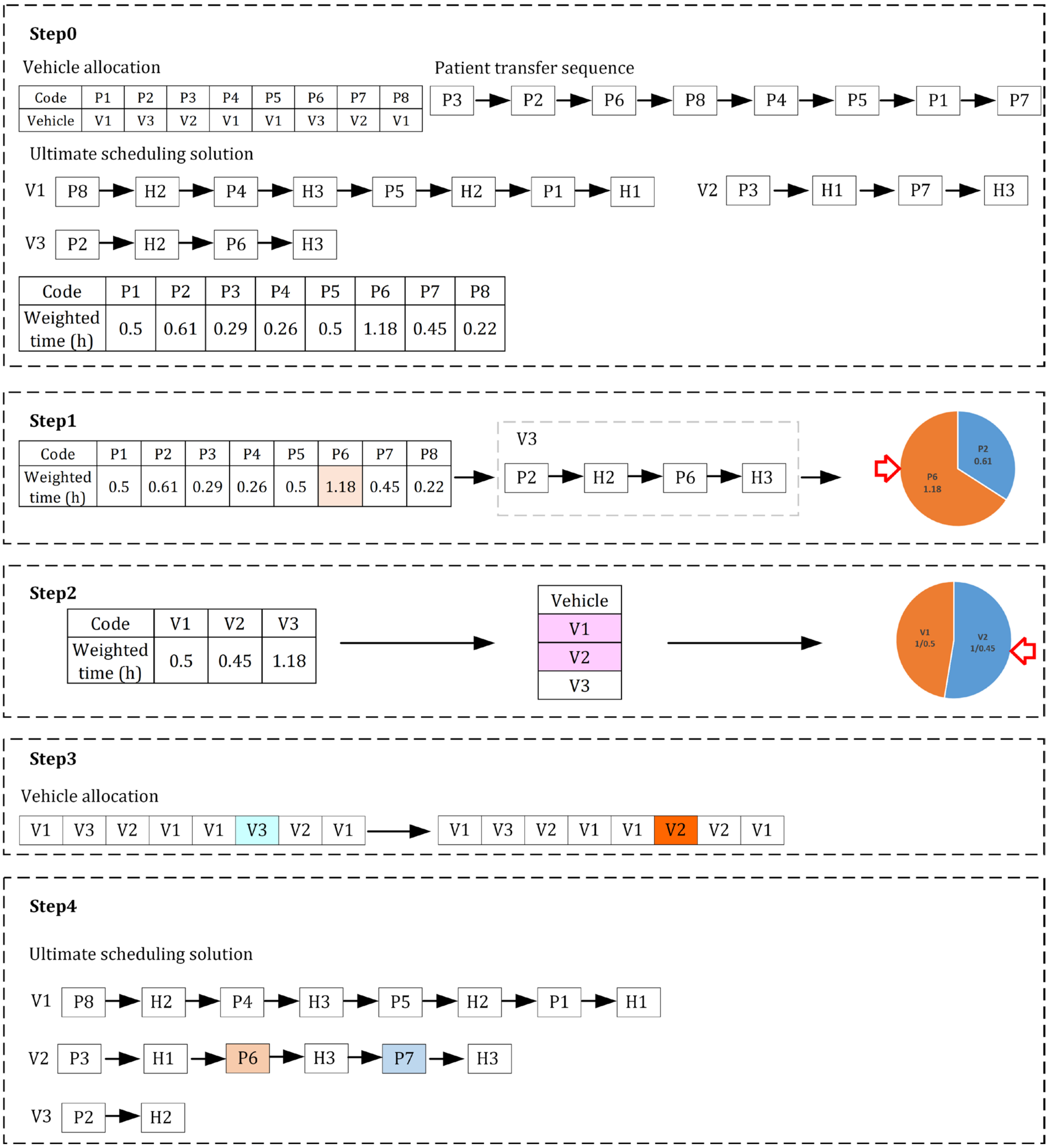

Fig. 5 The description of roulette selection strategy

5.3 Encoding example

The relative location indexing [44] based encoding solution is introduced to extend IQPSO to solve combinatorial optimization problems. Fig. 6 show an example of the encoding solution, respectively. In the proposed encoding solution, the particle has $2I$ dimensions, with the value range of each dimension in the first half being $[0, J]$ and the value range of each dimension in the latter half being $[0, K]$.

The coding solution can be described by the following steps.

First, when initializing the location s of particles in the context of patient-vehicle allocation, where the location in a specific dimension needs to be determined based on a random number, a random number is generated, rounded up and set as the initial location for that dimension. The vehicle information corresponding to the row index is then retrieved from the vehicle table, where the first rounded-up number corresponds to the first row in the vehicle table, representing the vehicle with the ID of 1, labeled "Code". This results in the vehicle allocation outcome as follows:

(1,1), (2,3), (3,2), (4,1), (5,1), (6,3), (7,2), (8,1). In this notation, (,)represents the patient ID and the row number in the vehicle table. For example, (3,1) indicates that $P3$ is assigned to the vehicle corresponding to the first row in the vehicle table. Furthermore, this leads to the specific vehicle assignments: $(P1, V1)$, $(P2, V3)$, $(P3, V2)$, $(P4, V1)$, $(P5, V1)$, $(P6, V3)$, $(P7, V2)$, $(P8, V1)$. In this case, "(,)" represents the patient's code and a specific vehicle arrangement in Subtable2.

Next, the hospital allocation for patients also needs to be determined based on a random number. A random number is generated, rounded up and set as the initial location for that dimension. The hospital information corresponding to the row index is then retrieved from the hospital table, resulting in the hospital allocation outcomes: (1,1), (2,2), (3,1), (4,3), (5,2), (6,3), (7,3), (8,2). In this case, "(,)" represents the patient's code and the row number in Subtable1 that corresponds to the hospital. For example, "(2,3)" indicates that $P2$ was treated at Hospital $H3$ in Subtable1 and by knowing the relative location n of the allocated hospital, we can further obtain the specific hospital information in that row: $(P1, H1)$, $(P2, H2)$, $(P3, H1)$, $(P4, H3)$, $(P5, H2)$, $(P6, H3)$, $(P7, H3)$, $(P8, H2)$. Here, (,) represents the patient ID and the specific hospital assigned, ultimately leading to the hospital allocation plan.

Subtable 1 Hospital condition form

Code	Name	Grade	Location
H1	Haidian Hospital	II	(116.3155,39.9766)
H2	The Third Hospital of Peking University	III	(116.3600,39.9827)
H3	Shangdi Hospital	II	(116.2987,40.0239)

Subtable 2 Vehicle condition form

Code	Name	Type	Velocity (km/h)	Available time (h)	Location
V1	Ambulance 1	Ambulance	72	0.00	(116.3264, 39.9620)
V2	Social vehicle 1	Social vehicle	50	0.17	(116.3123, 39.9451)
V3	Ambulance 2	Ambulance	72	0.33	(116.3478, 39.9726)

Subtable 3 Patient condition form

Code	Name	Sex	Age	Grade	Waiting time (h)	Location
P1	San Zhang	Male	60	III	0.05	(116.3152, 40.0215)
P2	Si Li	Female	61	III	0.1	(116.3220, 39.9700)
P3	Wu Wang	Female	66	II	0.02	(116.3257, 39.9639)
P4	Bing Cui	Male	67	I	0.03	(116.2970, 39.9855)
P5	Yi Liu	Female	77	II	0.13	(116.3285, 39.9887)
P6	Ding Li	Male	63	III	0.37	(116.3355, 39.9736)
P7	Geng Yang	Male	75	II	0.08	(116.2998, 40.0001)
P8	Wu Hou	Male	76	I	0.13	(116.3511, 39.9552)

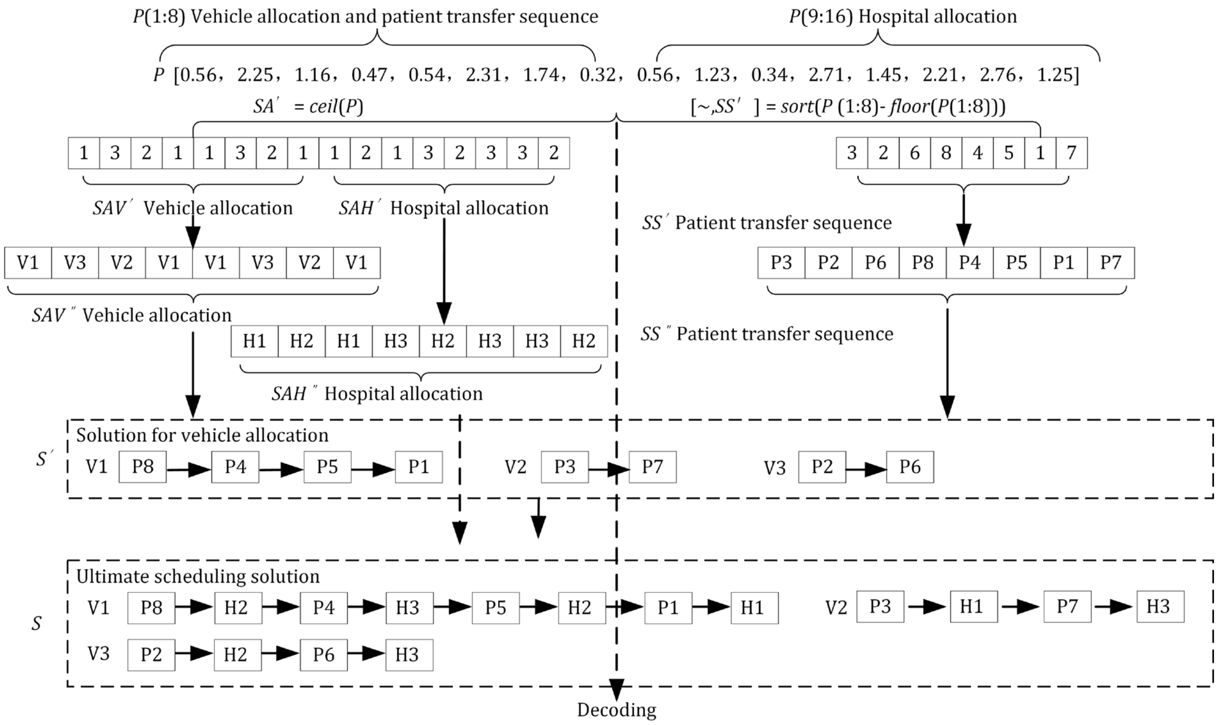

Fig. 6 The example of the encoding solution

Then, assuming that patients can receive treatment immediately upon arrival at the hospital, the only thing needed is to arrange the order of transportation for the patients. The decimal parts of each dimension in the first half of the particle are sorted to obtain the transportation order of the patients. In this encoding demonstration, the relative location index results of the treatment order are 8, 2, 1, 5, 6, 3, 7, 4, which corresponds to the specific order of patients: $P8$, $P2$, $P1$, $P5$, $P6$, $P3$, $P7$, $P4$.

After that, combining the allocation of patients to vehicles and the order of patient transportation, we can obtain the vehicle scheduling plan: $\{V1,(P8,P1,P5,P4)\}$; $\{V2,(P3,P7)\}$; $\{V3,(P2,P6)\}$. For example, $\{V3,(P2,P6)\}$ indicates that will first transport $P2$ and then $P6$.

Finally, by combining the patient-vehicle scheduling plan and the patient-hospital allocation plan, we can obtain the final scheduling plan: $\{V1{:}\,(P8,H2,P1,H1,P5,H2,P4,H3)$, $V2{:}\,(P3,H1,P7,H3)$, $V3{:}\,(P2,H2,P6,H3)\}$. For example, $\{V3,(P2,H2,P6,H3)\}$ indicates that $V3$ will transport $P2$ to $H2$ and then transport $P6$ to $H3$.

6. Case study

A numerical experiment is designed to evaluate the performance of the IQPSO. Benchmark instances are introduced, together with an encoding solution, to determine the parameters of the algorithm.

6.1 Case description

We provide a quantitative analysis to evaluate the proposed model and algorithm, comparing the fair solution with the system's optimum. We use Haidian District in Beijing as a case study; the system monitors 60 patients who require assistance. There are 7 hospitals available for scheduling within the district, including 3 hospitals of Level II and 4 hospitals of Level III. Additionally, the system has access to 20 rescue vehicles, comprising 15 ambulances and 5 taxis or e-taxis, all can be deployed.

Table 1 outlines the patients who need to be transferred to a hospital for treatment at that particular time. Table 2 presents the available hospitals in the network, located near the potential medical needs of the patients. Finally, Table 3 provides details on the vehicles assigned to transport patients from their homes to the hospitals. Fig. 7 illustrates the distribution of 60 patients, 20 vehicles and 7 hospitals in this case.

Table 1 Patient condition form

Code	Name	Sex	Age	Grade	Waiting time(h)	Location
1	San Zhang	Male	60	III	0.05	(116.3152, 40.0215)
2	Si Li	Female	61	III	0.10	(116.3220, 39.9700)
3	Wu Wang	Female	66	II	0.02	(116.3257, 39.9639)
4	Bing Cui	Male	67	I	0.03	(116.2970, 39.9855)
5	Yi Liu	Female	77	II	0.13	(116.3285, 39.9887)
6	Ding Li	Male	63	III	0.37	(116.3355, 39.9736)
7	Geng Yang	Male	75	II	0.08	(116.2998, 40.0001)
8	Wu Hou	Male	76	I	0.13	(116.3511, 39.9552)
9	Wu Liu	Female	80	III	0.20	(116.2743, 39.9820)
10	Liu Li	Male	63	I	0.00	(116.3487, 39.9789)
11	Fei Zhang	Female	76	III	0.05	(116.3524, 39.9200)
12	Tian Li	Female	75	II	0.00	(116.3009, 40.0244)
13	Bu Yang	Female	78	II	0.08	(116.2751, 39.9487)
14	Wen Yin	Male	65	III	0.20	(116.3642, 39.9778)
15	Peng Li	Male	79	I	0.35	(116.3256, 39.9443)
16	Li Cui	Female	63	III	0.00	(116.3165, 39.9752)
17	Li Li	Female	62	III	0.07	(116.2974, 39.9180)
18	Yi Song	Male	66	II	0.10	(116.3159, 39.9532)
19	Ren Wu	Male	70	I	0.12	(116.3741, 40.0015)
20	Di Wu	Female	71	I	0.18	(116.2804, 39.9367)

Table 1 (Continuation)

21	Da Zheng	Male	69	III	0.38	(116.3366, 40.0042)
22	Gang Wang	Female	73	II	0.00	(116.3565, 39.9690)
23	Zhou Zhou	Male	64	II	0.05	(116.2908, 39.9204)
24	Li Wang	Male	72	III	0.25	(116.3144, 39.9812)
25	Gu Yang	Female	78	II	0.10	(116.3299, 39.9956)
26	Fei Xu	Male	74	III	0.15	(116.3700, 39.9784)
27	Bing Yan	Female	72	I	0.08	(116.2952, 39.9502)
28	Sheng Chen	Male	66	III	0.15	(116.3258, 39.9623)
29	San Xu	Male	58	II	0.00	(116.3190, 39.9358)
30	Tou Zhu	Male	62	I	0.08	(116.3374, 40.0071)
31	Mau Ding	Male	61	III	0.22	(116.3111, 39.9494)
32	Ting Pan	Female	52	III	0.08	(116.3430, 39.9660)
33	Da Lu	Female	57	I	0.33	(116.2837, 39.9299)
34	Lu Wei	Female	71	II	0.13	(116.3253, 39.9707)
35	Tao Yang	Male	77	I	0.23	(116.3301, 39.9632)
36	Liu He	Male	73	III	0.42	(116.3456, 40.0019)
37	Bao Luo	Female	78	II	0.37	(116.2957, 39.9393)
38	Fang Cheng	Male	68	I	0.27	(116.3549, 39.9572)
39	Yang Wang	Female	70	II	0.00	(116.3103, 39.9330)
40	Zhen Fang	Male	62	III	0.03	(116.3182, 39.9851)
41	San Xiong	Male	66	III	0.10	(116.3387, 39.9467)
42	Qian Wan	Female	63	II	0.13	(116.3280, 39.9509)
43	Piao Bai	Male	71	III	0.27	(116.3434, 39.9744)
44	Jian Hao	Male	75	I	0.12	(116.2914, 40.0132)
45	Mao Jin	Female	67	III	0.08	(116.3077, 39.9706)
46	Tu Hu	Female	65	II	0.17	(116.3562, 39.9811)
47	Duo Yu	Male	69	III	0.03	(116.2758, 39.9383)
48	Niu Ma	Male	77	I	0.02	(116.3156, 39.9430)
49	Du Liu	Female	58	II	0.08	(116.3451, 40.0166)
50	Li Qin	Male	67	III	0.25	(116.2841, 39.9592)
51	Ge Fu	Male	66	III	0.37	(116.3398, 39.9763)
52	Hui Su	Female	62	II	0.10	(116.3287, 39.9485)
53	Mei Chen	Female	72	I	0.17	(116.2904, 40.0030)
54	Ke Niu	Male	59	III	0.05	(116.3576, 39.9663)
55	An Shi	Female	70	I	0.00	(116.3129, 39.9271)
56	Ying Yu	Female	72	II	0.07	(116.3217, 39.9912)
57	Jin Hu	Male	68	III	0.33	(116.3381, 40.0058)
58	Qiang Gao	Female	69	I	0.13	(116.2809, 39.9527)
59	Jin Niu	Female	67	III	0.10	(116.3142, 39.9848)
60	Xian Yang	Male	65	II	0.02	(116.3493, 39.9710)

Table 2 Hospital condition form

Code	Name	Grade	Location
1	Haidian Hospital	II	(116.3155,39.9766)
2	The Third Hospital of Peking University	III	(116.3600,39.9827)
3	Shangdi Hospital	II	(116.2987,40.0239)
4	Zhongguancun Hospital	II	(116.3206,39.9800)
5	Beijing 466 hospital	III	(116.3069,39.9637)
6	Peking University Hospital of stomatology	III	(116.3252,39.9523)
7	Peking University Cancer Hospital	III	(116.2897,39.9232)

Table 3 Vehicle condition form

Code	Name	Type	Velocity (km/h)	Available time (h)	Location
1	Ambulance1	Ambulance	72	0.00	(116.3264, 39.9620)
2	Ambulance2	Ambulance	72	0.13	(116.3478, 39.9726)
3	Social vehicles1	Social vehicles	50	0.12	(116.3123, 39.9451)
4	Ambulance3	Ambulance	72	0.37	(116.3332, 39.9538)
5	Ambulance4	Ambulance	73	0.00	(116.3294, 39.9964)
6	Ambulance5	Ambulance	72	0.20	(116.2905, 40.0120)

Table 3 (Continuation)

7	Social vehicles2	Social vehicles	50	0.10	(116.3368, 39.9489)
8	Ambulance6	Ambulance	72	0.05	(116.3436, 39.9801)
9	Social vehicles3	Social vehicles	50	0.42	(116.3114, 39.9712)
10	Ambulance7	Ambulance	72	0.08	(116.3002, 39.9231)
11	Ambulance8	Ambulance	72	0.03	(116.3523, 39.9875)
12	Social vehicles4	Social vehicles	50	0.02	(116.3199, 39.9307)
13	Ambulance9	Ambulance	72	0.17	(116.2996, 39.9557)
14	Ambulance10	Ambulance	72	0.17	(116.3344, 40.0180)
15	Ambulance11	Ambulance	72	0.03	(116.3605, 39.9823)
16	Ambulance12	Ambulance	72	0.05	(116.2929, 39.9482)
17	Social vehicles5	Social vehicles	50	0.02	(116.3105, 39.9768)
18	Ambulance13	Ambulance	72	0.07	(116.3268, 39.9648)
19	Ambulance14	Ambulance	72	0.11	(116.3539, 39.9611)
20	Ambulance15	Ambulance	72	0.05	(116.3120, 39.9845)

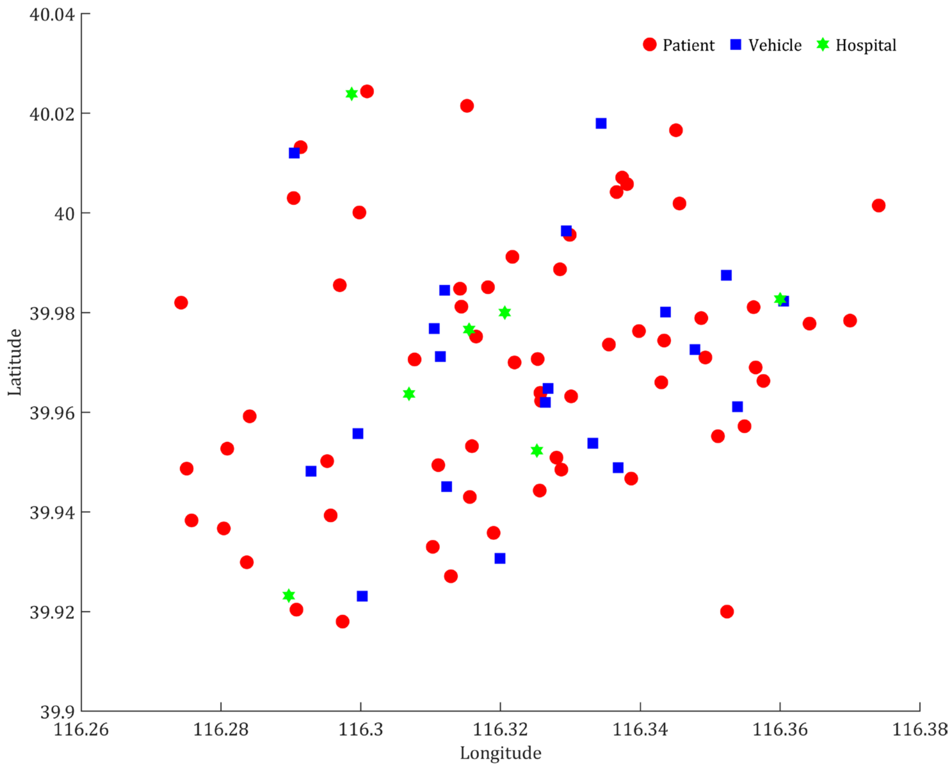

Fig. 7 The distribution of patients, vehicles and hospitals

6.2 Experimental design

The CQPSO proposed in [45] and the original QPSO [46-48] are selected for comparison. In IQPSO, the Cellular neighbor network structure adopts the Von Neumann neighborhood, the Moore neighborhood and the Extended Moore neighborhood, represented by IQPSO Von Neumann, IQPSO Moore and IQPSO Extended Moore, respectively. These algorithms are used to solve the case for comparison.

All selected algorithms are programmed in MATLAB. Each algorithm is applied to solve the Haidian district problem set and is run 30 times independently. The software environment for numerical experiments is the R2024b version of MATLAB. The hardware environment for numerical experiments is a laptop with a x64-processor Intel(R) Core (TM) i7-8550U CPU @ 1.80 GHz 1.99 GHz and 16 GB RAM.

6.3 Parameter settings

The parameters of the algorithms are set based on literature and experiments. The p and are d defined by [42], the β_{max} and β_{mim} are defined by [45] and the a is defined by [43]. The others are set according to the experiments. The parameters of the algorithms are shown in Table 4.

Table 4 The parameters of the algorithms

No	Name	Value	No	Name	Value	No	Name	Value
1	r	10	5	k	96	9	a	8
2	c	20	6	N_s	200	10	δ	10
3	p	0.5	7	β_{max}	1	11	Max $\_ite$	8000
4	d	5	8	β_{mim}	0.4			

6.4 Experimental result

The average convergence of the algorithms for the optimal solution of the case shown in Fig. 8. IQPSO with the three neighborhood structures (Von Neumann, Moore and Extended Moore) outperforms both CQPSO and QPSO in terms of convergence speed and overall performance. Among these, the Extended Moore neighborhood structure yields the best results, indicating that the choice of neighborhood structure significantly enhances the algorithm's performance. Compared to CQPSO and QPSO, IQPSO demonstrates superior performance, especially with the inclusion of the neighborhood structures. IQPSO achieves a lower fitness value in the long run, highlighting the benefits of incorporating the neighborhood structures.

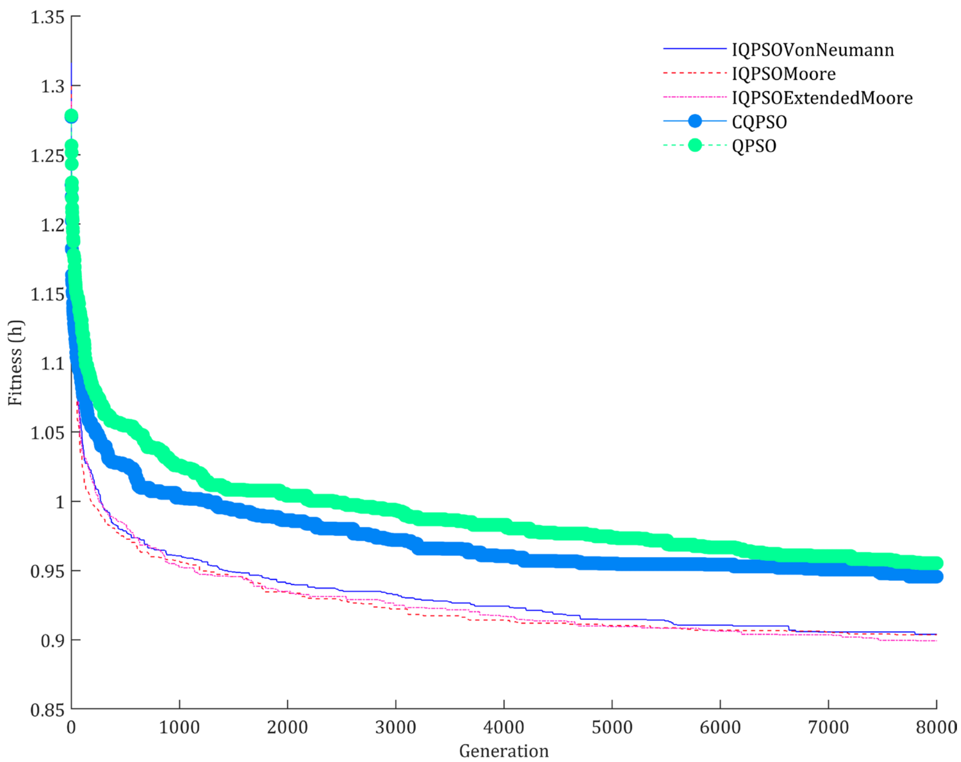

Fig. 8 The average convergence of the algorithms for the optimal solution of the case

Table 5 shows the results of different algorithms in the simulation model, including the minimum, maximum, mean and standard deviation. It can be observed that all algorithms have similar mean values, but there are differences in the maximum values and standard deviations, with the IQPSO series algorithms showing more stability. Fig. 9 shows the statistical analysis of the algorithms for the fitness for the case. The red + in Fig. 9 represents outliers. It can be seen from the figure that the various versions of IQPSO have better statistical performance and both of them are better than CQPSO and QPSO. Moreover, the Extended Moore neighborhood has better performance than the Von Neumann neighborhood and can obtain solutions that are closer to the optimal solutions of the benchmark instances. The Extended Moore neighborhood can reduce the convergence speed of the algorithm, which is beneficial to avoid the algorithm falling into the local optimal solution and is more likely to find the global optimal solution.

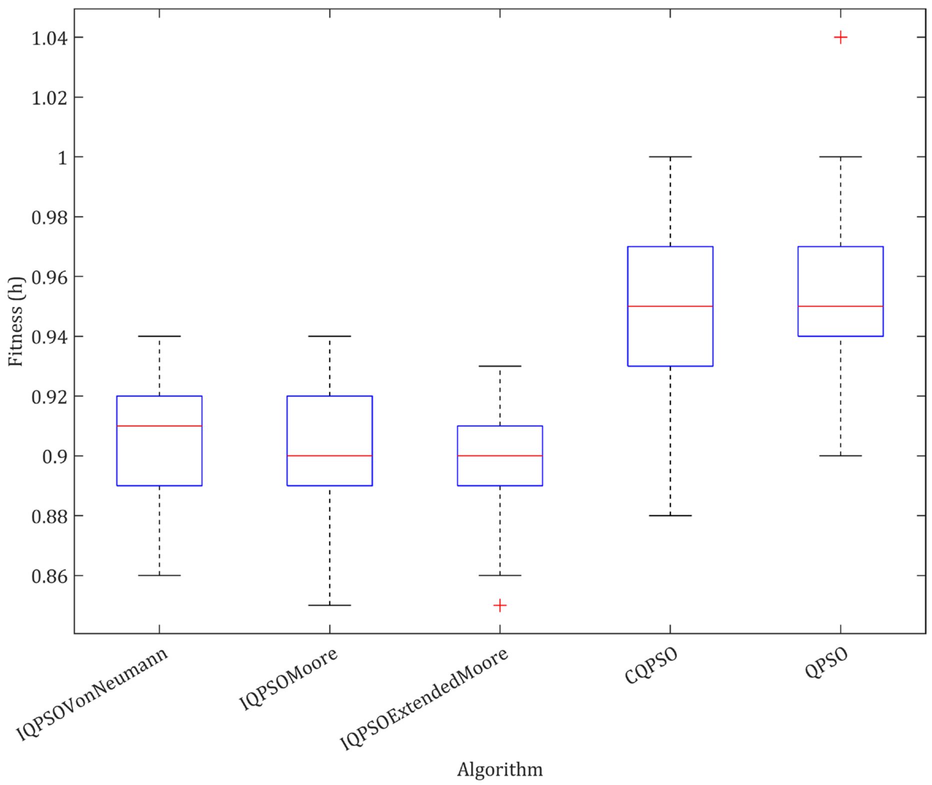

Fig. 9 The statistical analysis of the algorithms on the fitness for the case

Table 5 The computational statistics of the algorithms for the fitness of the case

Name	Min	Max	Mean	Std.
IQPSO Von Neumann	0.86	0.94	0.9	0.02
IQPSO Moore	0.85	0.94	0.9	0.02
IQPSO Extended Moore	0.85	0.93	0.9	0.02
CQPSO	0.88	1	0.95	0.03
QPSO	0.9	1.04	0.96	0.03

Fig. 10 shows the running time of IQPSO is almost double that of CQPSO and QPSO, but it can also obtain a sub-optimal solution in a reasonable time, which means it has a strong practical application value. The running time of IQPSO with various neighborhood structures is basically the same, different neighborhood structures have little effect on the algorithm running time.

Fig. 11 shows the weighted transportation time, that is, fitness for 60 patients. While the weighted transportation time is generally evenly distributed, some patients experience longer times. This suggests that, although the overall distribution is fairly uniform, individual patient needs and transportation routes contribute to variations. The data highlights the importance of optimizing the transportation scheduling process to reduce costs and improve efficiency. Fig. 12 shows the transportation time for 60 patients. The transportation process for each patient is divided into three stages: waiting time for system allocation (red), vehicle availability time (yellow) and transportation time, which is the time the vehicle reaches the patient (green). The data in the figure reflects the distribution of different time periods during the patient transfer process. Fig. 13 shows the Gantt chart of 60 patients (from P1 to P60), displaying the transfer situation for each vehicle. This chart highlights the patient allocation and vehicle scheduling the IQPSO, illustrating the performance during the transportation process.

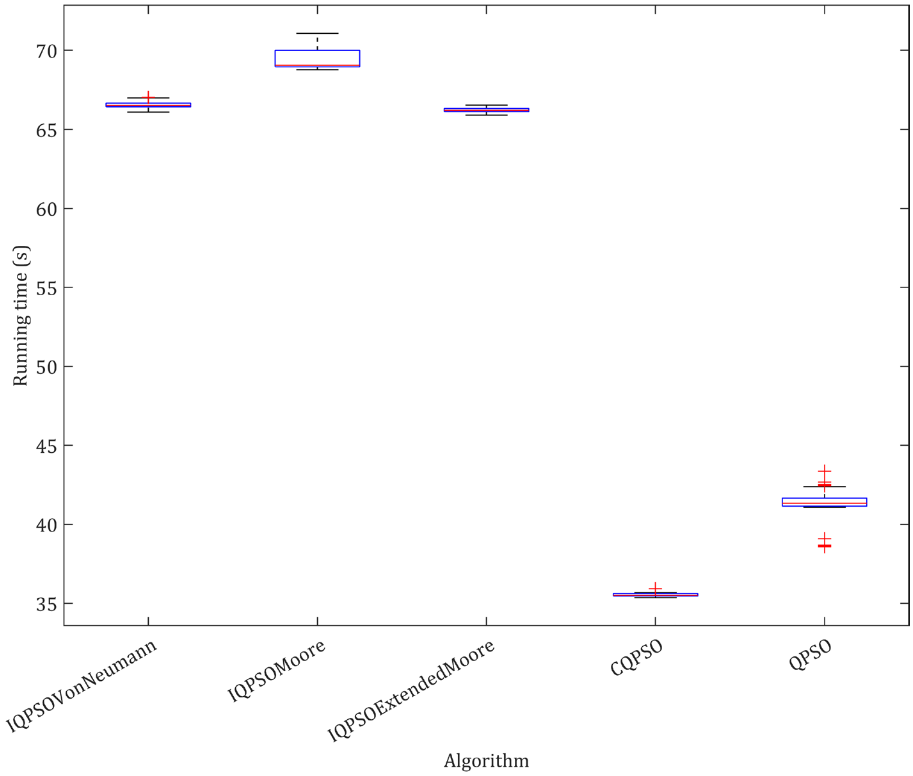

Fig. 10 The statistical analysis of the algorithms on the running time for the case

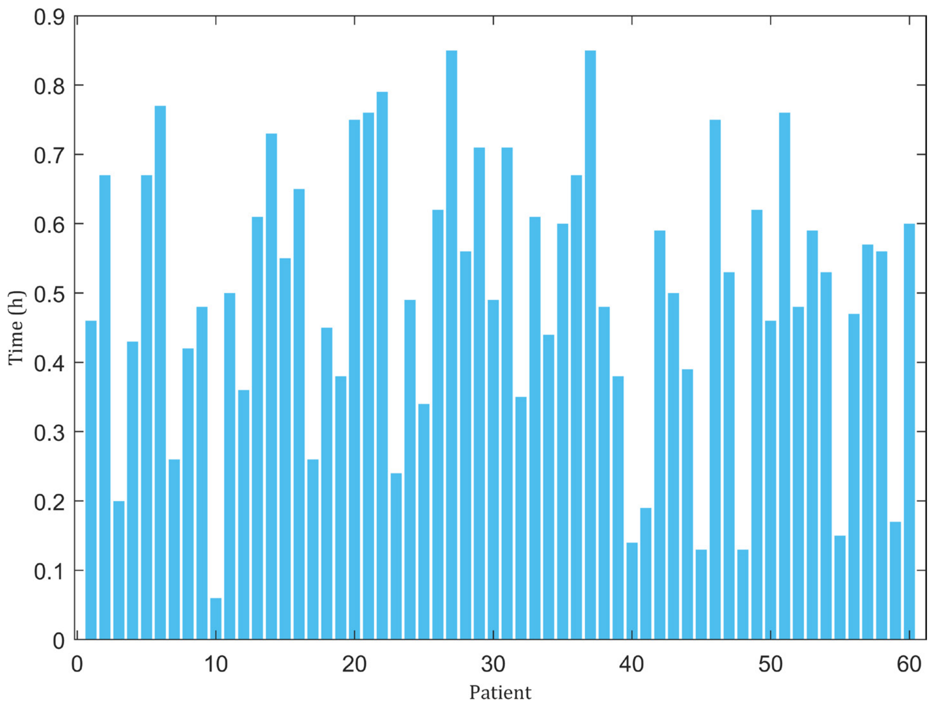

Fig. 11 The Gantt chart of fitness for the case with IQPSO Moore

Fig. 12 The Gantt chart of patient for the case with IQPSO Moore

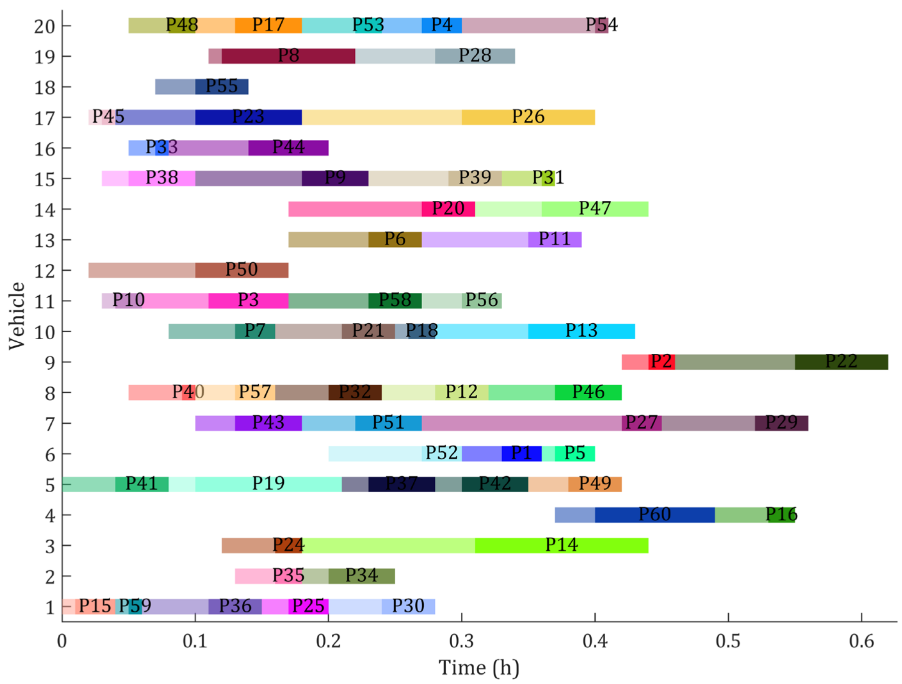

Fig. 13 The Gantt chart of Vehicle for the case with IQPSO Moore

7. Discussion

The EMTVHSP is addressed within the context of an emergency home health monitoring system. The system is designed around a comprehensive emergency management framework that incorporates wearable monitoring devices for elderly patients, as well as 5G, big data and other artificial intelligence technologies. It also includes a monitoring center and an emergency medical resource scheduling solution.

An innovation of the model is that it considers both the severity of the patient‘s condition and the waiting time to measure the rescue effect. Unlike traditional models that treat all patients equally, this model assigns weighted priorities based on the severity of each patient’s condition.

Specifically, the more critical the patient's condition and the longer their waiting time, the higher the priority and the faster they receive treatment. Additionally, the model considers the real-time availability of rescue vehicles, acknowledging that these vehicles are not always accessible.

To optimize the scheduling process within this model, an improved QPSO is proposed. This enhanced algorithm addresses the limitations of traditional methods in handling complex, dynamic events by improving the global search capability. The algorithm integrates small-world networks, such as the Von Neumann neighborhood, the Moore neighborhood and the Extended Moore neighborhood, which allows for better exploration of the solution space and increased solution diversity. The algorithm also incorporates multiple constraint-handling strategies—random generation, Pbx, Gbx and boundary values that ensure the feasibility and adaptability of the scheduling solutions. Furthermore, the improved QPSO addresses common issues such as premature convergence by introducing mutation operations based on individual historical stagnation and dynamically adjusted mutation probability. These modifications strengthen the algorithm's exploration ability during later iterations, allowing it to respond more effectively to changing emergency conditions. In terms of scheduling strategies, the algorithm employs a roulette-wheel mutation method to reassign patient transportation paths. This innovation helps to minimize transportation delays, thereby improving the efficiency of emergency responses.

Different neighborhood structures significantly affect IQPSO's convergence, optimal solution quality and running time. IQPSO Von Neumann converges quickly at first but slows down later, while IQPSO Moore and IQPSO Extended Moore demonstrate more stable convergence, with IQPSO Extended Moore balancing speed and stability. In terms of optimal solution quality, IQPSO Moore and IQPSO Extended Moore yield better results than IQPSO Von Neumann. IQPSO Von Neumann has a faster runtime, typically within 4 minutes for most benchmarks, while IQPSO Moore performs slightly slower but remains efficient with a runtime under 6 minutes. IQPSO outperforms both QPSO and CQPSO in convergence speed, solution quality and runtime. IQPSO reaches convergence faster and more reliably, especially in large-scale problems, compared to QPSO. IQPSO consistently produces higher-quality solutions. IQPSO also shows faster runtime (2-4 minutes for medium-sized problems), outperforming CQPSO, which takes longer, particularly when dealing with dynamic events.

The improvement is 5.6 % compared to the CQPSO and 6.7 % compared to the QPSO. These results show that the proposed system combined with the improved QPSO is well suited to meet the dynamic needs of emergency medical support. It has great potential for practical application in real-world scenarios involving emergency home health monitoring and patient transportation.

8. Conclusion

An improved QPSO is proposed for the EMTVHSP problem in EHMS. The EMTHDM aims to balance the real-time allocation of resources and minimize the maximum patient transit time, while also considering the rescue effect. Combined with the small world network theory, the global search strategy is improved, a variety of constraint processing strategies are introduced and the mutation probability and roulette mutation strategy are dynamically adjusted to improve the adaptability and stability of the algorithm. Experimental results show that the improved algorithm significantly outperforms traditional methods in terms of solution quality, reducing patient waiting time and optimizing resource utilization. The novel optimization approach for the dynamic scheduling of emergency resources is proposed, with great potential to enhance emergency response efficiency. This is highly significant for elderly patients. In the long term, it will help safeguard the health of the elderly and alleviate the pressures on social elderly care and medical systems. Meanwhile, the EMTVHSP problem is essentially a scheduling problem for medical emergency resources such as vehicles and hospitals. In principle, the method can be extended to other similar non-medical emergency scheduling, such as job shop scheduling problems in manufacturing. Future research can explore the cost of implementing EHMS and IQPSO in actual medical systems, compare the effects of IQPSO with other optimization methods such as deep learning and genetic algorithms, and evaluate the scalability of the model in large or multi-city medical networks. Additionally, the role of cybersecurity measures in data of wearable devices within EHMS, as well as the impact of varying traffic conditions on scheduling performance, can also be explored.

Acknowledgement

This work was supported by the Beijing Social Science Foundation [Grant number 21GLC044].

References

[1] Bao, J., Zhou, L., Liu, G., Tang, J., Lu, X., Cheng, C., Jin, Y., Bai, J. (2022). Current state of care for the elderly in China in the context of an aging population, *BioScience Trends*, Vol. 16, No. 2, 107-118, doi: 10.5582/bst.2022.01068.

[2] Ma, N., Feng, J., Geng, X., Zhao, W., Zhao, L., Bian, H., Wang, Y., Chen, W., Hou, Y., Chen, W., Zhan, Y., Liu, Y. (2024). Medical emergency response and management of tritium-related accidents, *ACS Chemical Health & Safety,* Vol. 31, No. 3, 180-185, doi: 10.1021/acs.chas.3c00061.

[3] Mojir, K.Y., Pilemalm, S. (2016). Actor-centred emergency response systems: A framework for needs analysis and information systems development, *International Journal of Emergency Management,* Vol. 12, No. 4, 403-434, doi: 10.1504/IJEM.2016.079844.

[4] Gupta, S., Starr, M.K., Farahani, R.Z., Matinrad, N. (2016). Disaster management from a POM perspective: Mapping a new domain, *Production and Operations Management*, Vol. 25, No. 10, 1611-1637, doi: 10.1111/poms.12591.

[5] Liang, B., Tao, Q., Gao, W., Ren, Q., Yao, X. (2023). Integrated the medical procedure analyze seismic resilience of healthcare system: A critical review from the resilience of healthcare system vs. medical demand perspective, *Advances in Civil Engineering*, Vol. 2023, No. 1, Article No. 4468383, doi: 10.1155/2023/4468383.

[6] Xu, W., Xu, S., Liu, D.Y., Awaga, A.L., Rabia, A., Zhang, Y.Y. (2024). Impact of fairness concerns on resource-sharing decisions: A comparative analysis using evolutionary game models in manufacturing enterprises, *Advances in Production Engineering & Management*, Vol. 19, No. 2, 223-238, doi: 10.14743/apem2024.2.503.

[7] Liu, Y., Cui, N., Zhang, J. (2019). Integrated temporary facility location and casualty allocation planning for post-disaster humanitarian medical service, *Transportation Research Part E: Logistics and Transportation Review*, Vol. 128, 1-16, doi: 10.1016/j.tre.2019.05.008.

[8] Zhu, M., Wang, Z., Liu, H., Li, Y., Yu, D. (2024). Numerical modeling of elastic waves using the random-enhanced QPSO algorithm, *Applied Geophysics*, Vol. 21, No. 1, 80-92, doi: 10.1007/s11770-021-0964-5.

[9] Wang, B., Zhang, Z., Song, Y., Chen, M., Chu, Y. (2023). Application of Quantum Particle Swarm Optimization for task scheduling in Device-Edge-Cloud Cooperative Computing, *Engineering Applications of Artificial Intelligence*, Vol. 126, Part C, Article No. 107020, doi: 10.1016/j.engappai.2023.107020.

[10] Utami, I.Q., Ramdani, F. (2022). GEMAR: Web-based GIS for emergency management and ambulance routing, *Informatics for Health and Social Care*, Vol. 47, No. 2, 123-131, doi: 10.1080/17538157.2021.1948856.

[11] Mehmood, A., Rowther, A.A., Kobusingye, O., Hyder, A.A. (2018). Assessment of pre-hospital emergency medical services in low-income settings using a health systems approach, *International Journal of Emergency Medicine*, Vol. 11, No. 1, Article No. 53, doi: 10.1186/s12245-018-0207-6.

[12] Shah, M.N. (2006). The formation of the emergency medical services system, *American Journal of Public Health*, Vol. 96, No. 3, 414-423, doi: 10.2105/AJPH.2004.048793.

[13] Boujemaa, R., Jebali, A., Hammami, S., Ruiz, A., Bouchriha, H. (2018). A stochastic approach for designing two-tiered emergency medical service systems, *Flexible Services and Manufacturing Journal*, Vol. 30, 123-152, doi: 10.1007/s10696-017-9286-6.

[14] Li, X., Li, Y. (2012). A model on emergency resource dispatch under random demand and unreliable transportation, *Systems Engineering Procedia*, Vol. 5, 248-253, doi: 10.1016/j.sepro.2012.04.039.

[15] Du, L. (2020). Medical emergency resource allocation model in large-scale emergencies based on artificial intelligence: Algorithm development, *JMIR Medical Informatics*, Vol. 8, No. 6, Article No. e19202, doi: 10.2196/19202.

[16] Yoon, S., Albert, L.A., White, V.M. (2021). A stochastic programming approach for locating and dispatching two types of ambulances, *Transportation Science*, Vol. 55, No. 2, 275-296, doi: 10.1287/trsc.2020.1023.

[17] Rolland, E., Patterson, R.A., Ward, K., Dodin, B. (2010). Decision support for disaster management, *Operations Management Research*, Vol. 3, 68-79, doi: 10.1007/s12063-010-0028-0.

[18] Li, K., Li, D., Ma, H.Q. (2023). An improved discrete particle swarm optimization approach for a multi-objective optimization model of an urban logistics distribution network considering traffic congestion, *Advances in Production Engineering & Management*, Vol. 18, No. 2, 211-224, doi: 10.14743/apem2023.2.468.

[19] Zhang, F.L. (2024). Evolutionary algorithm for dynamic resource allocation and its applications, *International Journal of Simulation Modelling*, Vol. 23, No. 3, 531-542, doi: 10.2507/IJSIMM23-3-CO14.

[20] Kovacic, M., Brezocnik, M. (2018). Reduction of surface defects and optimization of continuous casting of 70MnVS4 steel, *International Journal of Simulation Modelling*, Vol. 17, No. 4, 667-676, doi: 10.2507/IJSIMM17(4)457.

[21] Rabbani, M., Oladzad-Abbasabady, N., Akbarian-Saravi, N. (2022). Ambulance routing in disaster response considering variable patient condition: NSGA-II and MOPSO algorithms, *Journal of Industrial and Management Optimization*, Vol. 18, No. 2, 1035-1062, doi: 10.3934/jimo.2021007.

[22] Zhang, Y., Liu, J. (2021). Emergency logistics scheduling under uncertain transportation time using online optimization methods, *IEEE Access*, Vol. 9, 36995-37010, doi: 10.1109/ACCESS.2021.3061454.

[23] Wang, Y., Chen, X., Wang, L. (2023). Deep reinforcement learning-based rescue resource distribution scheduling of storm surge inundation emergency logistics, *IEEE Transactions on Industrial Informatics*, Vol. 19, No. 10, 10004-10013, doi: 10.1109/TII.2022.3230691.

[24] Yoon, S., Albert, L.A. (2021). Dynamic dispatch policies for emergency response with multiple types of vehicles, *Transportation Research Part E: Logistics and Transportation Review*, Vol. 152, Article No. 102405, doi: 10.1016/j.tre.2021.102405.

[25] Chou, C.-C., Chiang, W.-C., Chen, A.Y. (2022). Emergency medical response in mass casualty incidents considering the traffic congestions in proximity on-site and hospital delays, *Transportation Research Part E: Logistics and Transportation Review*, Vol. 158, Article No. 102591, doi: 10.1016/j.tre.2021.102591.

[26] Liu, J., Bai, J., Wu, D. (2021). Medical supplies scheduling in major public health emergencies, *Transportation Research Part E: Logistics and Transportation Review*, Vol. 154, Article No. 102464, doi: 10.1016/j.tre.2021.102464.

[27] Yazdani, M., Haghani, M. (2023). Optimisation-based integrated decision model for ambulance routing in response to pandemic outbreaks, *Progress in Disaster Science*, Vol. 18, Article No. 100288, doi: 10.1016/j.pdisas.2023.100288.

[28] Li, S.-H., Cheng, K.-A., Lu, W.-H., Lin, T.-C. (2012). Developing an active emergency medical service system based on WiMAX technology, *Journal of Medical Systems*, Vol. 36, No. 5, 3177-3193, doi: 10.1007/s10916-011-9809-8.

[29] Tang, Z., Sun, J. (2018). Multi objective optimization of railway emergency rescue resource allocation and decision, *International Journal of System Assurance Engineering and Management*, Vol. 9, No. 3, 696-702, doi: 10.1007/s13198-017-0648-y.

[30] Jotshi, A., Gong, Q., Batta, R. (2009). Dispatching and routing of emergency vehicles in disaster mitigation using data fusion, *Socio-Economic Planning Sciences*, Vol. 43, No. 1, 1-24, doi: 10.1016/j.seps.2008.02.005.

[31] Pătrașcu, A., Toader, F.A., Bălăcescu, A. (2024). An improved multi-objective hybrid algorithm for solving job shop scheduling problem, *Economic Computation and Economic Cybernetics Studies and Research*, Vol. 58, No. 3, 177-192, doi: 10.24818/18423264/58.3.24.11.

[32] Zhu, L., Gong, Y., Xu, Y., Gu, J. (2019). Emergency relief routing models for injured victims considering equity and priority, *Annals of Operations Research*, Vol. 283, 1573-1606, doi: 10.1007/s10479-018-3089-3.

[33] Du, H., Chen, J. (2023). An improved ant colony algorithm for new energy industry resource allocation in cloud environment, *Tehnički Vjesnik–Technical Gazette*, Vol. 30, No. 1, 153-157, doi: 10.17559/TV-20220712164019.

[34] Wang, S., Liu, F., Lian, L., Hong, Y., Chen, H. (2018). Integrated post-disaster medical assistance team scheduling and relief supply distribution, *The International Journal of Logistics Management*, Vol. 29, No. 4, 1279-1305, doi: 10.1108/IJLM-06-2017-0152.

[35] Tarhan, İ., Zografos, K.G., Sutanto, J., Kheiri, A., Suhartanto, H. (2023). A multi-objective rolling horizon personnel routing and scheduling approach for natural disasters, *Transportation Research Part C: Emerging Technologies*, Vol. 149, Article No. 104029, doi: 10.1016/j.trc.2023.104029.

[36] Li, H., Han, S., Wu, X., Wang, F. (2023). A novel task of loading and computing resource scheduling strategy in internet of vehicles based on dynamic greedy algorithm, *Tehnički Vjesnik–Technical Gazette,* Vol. 30, No. 4, 1298-1307, doi: 10.17559/TV-20221207032927.

[37] Moreno, A., Alem, D., Gendreau, M., Munari, P. (2020). The heterogeneous multicrew scheduling and routing problem in road restoration, *Transportation Research Part B: Methodological*, Vol. 141, 24-58, doi: 10.1016/j.trb.2020.09.002.

[38] Bodaghi, B., Palaneeswaran, E. (2016). An optimization model for scheduling emergency operations with multiple teams, In: *Proceedings of the 2016 International Conference on Industrial Engineering and Operations Management,* Detroit, Michigan, USA, 436-442.

[39] Srivastava, G., Singh, A. (2023). An evolutionary approach comprising tailor-made variation operators for rescue unit allocation and scheduling with fuzzy processing times, *Engineering Applications of Artificial Intelligence*, Vol. 123, Part A, Article No. 106246, doi: 10.1016/j.engappai.2023.106246.

[40] Heppner, F., Grenander, U. (1990). A stochastic nonlinear model for coordinated bird flocks, In: Krasner, S. (ed.), *The ubiquity of chaos,* AAAS, Washington, USA, 233-238.

[41] Kennedy, J., Eberhart, R. (1995). Particle swarm optimization, In: *Proceedings of ICNN'95 - International Conference on Neural Networks,* Perth, Australia, 1942-1948, doi: 10.1109/ICNN.1995.488968.

[42] Li, X., Li, X., Yang, L., Li, J. (2018). Dynamic route and departure time choice model based on self-adaptive reference point and reinforcement learning, *Physica A: Statistical Mechanics and its Applications*, Vol. 502, 77-92, doi: 10.1016/j.physa.2018.02.104.

[43] Zhang, Y., Gong, D.-W., Ding, Z. (2012). A bare-bones multi-objective particle swarm optimization algorithm for environmental/economic dispatch, *Information Sciences*, Vol. 192, 213-227, doi: 10.1016/j.ins.2011.06.004.

[44] Marinakis, Y., Marinaki, M. (2012). A hybrid particle swarm optimization algorithm for the open vehicle routing problem, In: Dorigo, M. (ed.), *Swarm Intelligence, ANTS 2012, Lecture Notes in Computer Science*, Vol. 7461, Springer, Berlin, Germany, 180-187, doi: 10.1007/978-3-642-32650-9_16.

[45] Singh, M.R., Mahapatra, S.S. (2016). A quantum behaved particle swarm optimization for flexible job shop scheduling, *Computers & Industrial Engineering*, Vol. 93, 36-44, doi: 10.1016/j.cie.2015.12.004.

[46] Sun, J., Feng, B., Xu, W. (2004). Particle swarm optimization with particles having quantum behavior, In: *Proceedings of the 2004 Congress on Evolutionary Computation*, Portland, USA, 325-331, doi: 10.1109/CEC.2004.1330875.

[47] Sun, J., Xu, W., Feng, B. (2005). Adaptive parameter control for quantum-behaved particle swarm optimization on individual level, In: *Proceedings of IEEE Conference on Cybernetics and Intelligent Systems,* Waikoloa, USA, 3049-3054, doi: 10.1109/ICSMC.2005.1571614.

[48] Sun, J., Xu, W., Feng, B. (2004). A global search strategy of quantum-behaved particle swarm optimization, In: *Proceedings of IEEE Conference on Cybernetics and Intelligent Systems,* Singapore, 111-116, doi: 10.1109/ICCIS.2004.1460396.