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Evacuation path optimization based on quantum ant colony algorithm

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ABSTRACT

Evacuation planning contains more than a few decisions which have to be made in a very short period of time and in the most appropriate way. Evacuation path optimization has vital importance in reducing the human and social harm and saving the aid time. Significant research efforts have been made in the literature to deal with evacuation optimization on the basis of deterministic optimization model, nevertheless the stochastic aspects or uncertainty of real-world evacuation have not been taken into account comprehensively. Inspired by the promising performance of heuristic algorithms to solve combinatorial problems, this paper proposes an improved quantum ant colony algorithm (QACA) for exhaustive optimization of the evacuation path that people can evacuate from hazardous areas to safe areas. In comparison with ACO (ant colony optimization) based method, QACA has the capability of finding a good solution faster using fewer individuals and possesses strong robustness, as a result of the quantum representation and updating of pheromone. Experiment results show that the proposed approach executes more effectively during evacuation.

1. Introduction

Swarm intelligence (SI) is based on natural biome communities, which has been used in various engineering applications due to its desirable properties of being adaptive, scalable, and robust [1]. The SI framework encompasses other popular frameworks such as Ant Colony Optimization (ACO) [2], and Particle Swarm Optimization (PSO) [3]. ACO is inspired from the foraging behavior of real world ant colonies, where ants release chemicals, i.e., pheromone on the route so as to mark the routes from the nest to food which would be followed by other members of the colony [4]. As a simulation evolution algorithm with typical swarm intelligence features, ACO is used to solve some complicated NP hard combinatorial optimization problems [5]. The ACO has experienced a tremendous growth, and its diverse applications include traffic congestion control [6], data mining [7], job-shop scheduling [8], and manufacturing [9].

Since evacuation methods have critical applications, scholars have carried out extensive and in-depth researches, and various approaches have been proposed and developed to deal with the evacuation problem [10]. A crowd is expected to move from areas impacted by accidents, terror attacks and other emergency events to safe zones, in short time and in the most appropriate way. However, urban evacuation is a complex adaptive system, as a mass of personnel interactions are involved [11]. Group belongingness, self-organization, and other motion characteristics of how evacuees behave during evacuation have many things in common with ant colony system. If affected by other ants in the colony, the ant would gradually tend to move along the route passed by most of the ants. Such herd behavior is in accordance with small group phenomenon of evacuees. In ACO, individuals' perception and interaction with the environment is represented by positive feedback mechanism, which, together with communication mechanism, are important foundations of the ACO algorithm. Therefore, the ACO algorithm provides a suitable solution to evacuation path optimization regardless of some limitations such as slow astringency, earlier stagnation.

The objective of this work is to design an evacuation path optimization method with high efficiency and strong robustness. This paper introduces the basic concepts and principles of quantum-inspired evolutionary algorithm (QEA) [12] into ACO, and proposes a quantum-inspired ACO algorithm for evacuation path optimization, called quantum ant colony algorithm (QACA). A quantum bit (Q-bit) is used to represent current pheromone information of the ant, and the quantum rotation gate is adopted to update pheromone. Similar to the general evolutionary algorithms, the QACA is characterized by the individuals, the evaluation function, and the

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population. However, instead of using binary or numeric representation, the QACA uses quantum bit to represent the population. When measuring the population fitness, a binary solution (represented by binary bits) is made by observing the quantum states. Although the basis of QACA is the concept and rules of quantum computing, this approach is an evolutionary algorithm rather than a quantum algorithm.

The rest of this paper is organized as follows. Section 2 provides a literature review. Section 3 sheds light on the evacuation problem. Section 4 elucidates an approach for evacuation path optimization based on QACA. Section 5 illustrates some experimental results. Section 6 presents conclusions and discusses some potential further work.

2. Literature review

Path optimization plays a significant role in evacuation, and affects the standard to measure whether an evacuation plan is feasible. On the other hand, evacuation path planning is one kind of path optimization and network flow problems. Therefore, this section covers the literature review on path optimization in general with some focus on applications to evacuation.

While there are various approaches proposed and developed in the literature to deal with evacuations, most of them are based on mathematical modeling, simulation, and soft computing.

Network flow models have been widely used in path optimization. Typically, there are two kinds of networks, i.e., dynamic and static. Dunn et al. [13] presented the maximum flow method for evacuation route within the permitted scope of network capacity. However, a network varies with time in real evacuation scenarios. Cova et al. [14] took into consideration the conflicts within intersections on a lane-based static network. In comparison with static models, dynamic models have some superiority in reflecting the time-varying characteristics. In [15], evacuation schemes, including vehicle allocation plans and routing strategies, are determined by an interval parameter fuzzy evacuation management model. Due to the uncertainty and complexity of the environment in emergency, such models have serious limitations in dealing with the evacuation process based on individual behaviors.

A considerable number of evacuation solutions rely on simulation models. Earlier simulation software tools include OREMS, DYNEV, VISSIM, and CORSIM. Subsequently, agent-based approaches have been proposed and developed [16,17]. Agents are generated to simulate the behavior of individuals, and accordingly a society system is built through interactive mechanisms among multi-agents. Such approaches could combine organically the microscopic behavior of individuals in a complex evacuation system with the macroscopic features of the system. In [18], an agent-based technique was used to model traffic flows at the level of individual vehicles, further to explore the effectiveness of simultaneous and staged evacuation strategies under different road network structures. Using an agent-based model, Lei et al. [19] simulated the evacuation process in different cases to investigate the effects of occupant density, exit width and automatic fare gates on evacuation time. They concluded that there is a linear relationship between occupant density and evacuation time. The human congestion problem in evacuation is considered in [20], and a distributed guiding navigation protocol was presented to balance the load of moving objects among multiple navigation paths to different exits. Chen et al. [21] proposed a distributed path planning algorithm for sensor network navigation in dynamic hazardous environments, and they constructed a distributed in-network directed navigation graph by using geographic or virtual coordinates of sensors based on a partial reversal method for directed acyclic graphs. Oxendine et al. [22] presented a network-based methodology to provide additional analytic support to emergency services personnel. In addition, a multi-objective, multi-criteria approach was used to determine optimum evacuation routes by using mobile phones. Ren et al. [23] combined the processes of evacuation route planning and traffic signal designing into an integrated model for evacuation, considering uncertain background demands.

Soft computing based intelligent algorithms provide new insights to deal with the evacuation problem. Common intelligent algorithms for evacuation path optimization include neural network algorithms [24], genetic algorithms [25], and swarm intelligence algorithms [26]. Introduced by Marco Dorigo in his Ph.D. thesis (1992), ACO is one of the most representative swarm intelligence algorithms, acting as an important nature-inspired stochastic metaheuristic for hard optimization problems [27]. Forcael et al. [28] developed an ACO algorithm to optimize the evacuation times during tsunamis, further to ensure safe routes. Rahman et al. [29] modified the ACO algorithm by creating exit sign, an agent, to determine the feasible route and guide occupants during the evacuation. They also considered physical obstacles during building evacuation in transitional probability rule of ACO. Zong et al. [30,31] presented a multi-objective ant colony optimization model to solve massive evacuation problems under complex traffic conditions, and a multi-ant colony system was developed to tackle mixed traffic evacuation problems. An improved ACO-based evacuation system was proposed in [32], which uses deodorant pheromone as a new guidance mechanism to erase ACO pheromone traces when dangerous locations are found.

Based on the existing literature, this paper proposes an improved ACO approach called quantum ant colony algorithm (QACA) to cover the exhaustive optimization of the evacuation path that people can evacuate from hazardous areas to safe areas. In order to construct an evacuation optimization method with better performance, QACA integrates the properties of ACO and quantum-inspired evolutionary algorithm (QEA) [33,34].

3. Description of the evacuation problem

This section introduces an intelligible way to build an evacuation network in order to simulate real-world situations. The evacuation problem will be represented as a network flow problem with certain constraints. Based on nodes and arc segments of graph theory, a graph, i.e., $G(N, A)$ needs to be defined with sources and sinks to emulate the flow of evacuees. Inside the buildings, nodes are used to describe rooms, corridors, stairs and halls, arc segments represent the links between the nodes. And likewise, every accessible area, in the outdoors, such as roads, squares, lawns, pavements are represented as nodes, and every link between two neighbor nodes denotes an arc segment.

Thus, a directed digraph $G(N, A)$ is used to represent a network of the evacuation area, where N denotes the set of nodes, and A is the set of links between two nodes. Several nodes are chosen to construct the set of origination nodes, O, while another part of them forms the set of destination nodes, D, and the others are intermediate nodes. Fig. 1 illustrates an evacuation network topology with 18 nodes and 32 links.

The objective of evacuation planning is to find a solution which minimizes the total time that all evacuees finish moving from dangerous zones to safe places. Consequently, time is the most significant factor that should be considered in the evacuation process. In this paper, the objectives are to minimize the total evacuation time of all evacuees and to balance the load of the whole evacuation network.

Following are definitions of some variables and parameters:

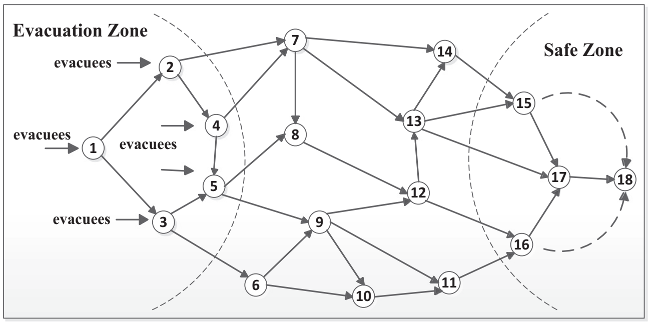


Fig. 1. The evacuation network topology.

T – a variable that shows the current moment of evacuation.
i – index of network nodes.
M – number of evacuees.
l_{ij} – length of the link between nodes i and j.
t_{ij}^k – time transferring through link ij of evacuee k.
$path_k$ – evacuation path of evacuee k.
$density_{ij}$ – density of evacuees on link ij.
s_0^k – the initial node of evacuee k.
$v_{ij}^k(T)$ – the speed of evacuee k on link ij.
$v_{ij}(0)$ – evacuation speed on link ij under normal conditions.
$N_{ij}(T)$ – number of evacuees on link ij.
C_{ij} – maximum capacity of link ij.

The optimization problem can be described as:

$$\min\ f_1 = \sum_{k=1}^{M} \sum_{i=s_0^k}^{j=\text{path}_k} t_{ij}^k \tag{1}$$

$$\min\ f_2 = \sum_{k=1}^{M} \sum_{i=s_0^k}^{j=\text{path}_k} \text{density}_{ij} \tag{2}$$

$$\text{density}_{ij} = \frac{N_{ij}(T)}{l_{ij}} \tag{3}$$

$$v_{ij}^k(T) = v_{ij}(0)e^{-w\cdot density_{ij}\cdot T} \tag{4}$$

$$\int_0^{t_{ij}^k} v_{ij}^k(T)dT = l_{ij} \tag{5}$$

Subject to:

$$\frac{N_{ij}(T)}{C_{ij}\cdot T} \leqslant 1 \tag{6}$$

The objective (1) is to minimize total evacuation time, and the objective (2) is to minimize total density of all paths. Eq. (3) is the formula of density along an arc segment. Eq. (4) is the function of the evacuation speed of evacuee k on link ij, where the value of speed decreases gradually according to the density of link ij, and w is a parameter which controls the decreasing rate. Eq. (5) describes the relation between $v_{ij}^k(T)$ and l_{ij}. Constraint (6) ensures that the total number of evacuees at link ij at time T will not exceed the maximum capacity of link ij.

Actually, both the weighted method and the reference point method are effective in contributing to Pareto optimal solutions of multi-objective nonlinear optimization problems. In this paper, the weighted ideal point method [38] is used to deal with the multi-objective problem. The Pareto optimal solution can be obtained by solving the single objective optimization problem below

$$\min\ F, \text{s.t.}(3)-(6)$$
$$F = c_1\left(\frac{f_1 - f_1^{\min}}{f_1^{\min}}\right)^2 + c_2\left(\frac{f_2 - f_2^{\min}}{f_2^{\min}}\right)^2 \tag{7}$$

where the vector $f^{\min} = (f_1^{\min}, f_2^{\min})$ is the ideal point, (c_1, c_2) is a pair of weight factors, and $c_1 + c_2 = 1,\ c_1 > 0, c_2 > 0$, for instance $(0.7, 0.3)$.

4. Optimization method for evacuation path

4.1. ACO algorithm based path planning

In ACO algorithms, the computational resources are assigned to a group of artificial ants (agents) that explore and construct solutions to the considered problem. The process of construction is a consequence of the ants' collaboration. Every ant makes decision on the next movement of its construction path according to the state transition rule [2], which will be introduced in the following.

In each node i, the ant moves to the node j in line with a random-proportional rule shown in (8).

$$P_{ij}^k = \begin{cases} \frac{\tau_{ij}^{\mu}(t)\eta_{ij}^{v}(t)}{\sum \tau_{ij}^{\mu}(t)\eta_{ij}^{v}(t)}, & j \in U \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

where U is a set of nodes that have not been visited before; $\tau_{ij}(t)$ represents the pheromone remained in the link between the nodes i and j; η_{ij} represents the heuristic information which is defined as $1/d_{ij}$; d_{ij} is the length of the link between the nodes i and j. The weight of pheromone and heuristic information are denoted by parameter μ and v, respectively, which influence the tendency towards new route against detected route. And t represents iterations.

The pheromone updates in every search cycle, and the updating rules are introduced in Eqs. (9) and (10),

$$\tau_{ij}(t+1) \leftarrow \rho\tau_{ij}(t) + \Delta\tau_{ij} \tag{9}$$

where ρ is the pheromone decay parameter, $0 < \rho < 1$; $\Delta\tau_{ij}$ represents the amount of pheromone left on the link ij, $\Delta\tau_{ij} = \sum \Delta\tau_{ij}^k$,

$$\Delta\tau_{ij}^k = \begin{cases} C/F_k, & k \text{ passed link } ij \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

where $\Delta\tau_{ij}^k$ represents the pheromone that the ant k left on the link ij; C is a constant.

The main steps of ACO algorithm for path planning are shown in Fig. 2.

4.2. QACA algorithm based path optimization

4.2.1. Basic concepts and techniques

This subsection introduces some basic concepts and techniques of QEA in details, such as the quantum bit, and the quantum rotation gate, which are the basis of the proposed algorithm.

In the classical QEA [12], the smallest information unit is Q-bit, which is constructed by two Eigen state $|0\rangle$ and $|1\rangle$, or an arbitrary superposition state of them, i.e., $|\varphi_i\rangle = \alpha_i|0\rangle + \beta_i|1\rangle,\ i = 1, 2, \ldots n$. α and β are a pair of complex numbers that specify the probability amplitudes of state $|0\rangle$ and state $|1\rangle$. The probabilities of Q-bit in state $|0\rangle$ and $|1\rangle$ are respectively defined as $|\alpha|^2$ and $|\beta|^2$ with $|\alpha|^2 + |\beta|^2 = 1$.

A population with m individuals is defined as $Q = (q_1, q_2, \ldots, q_j, \ldots, q_m)$, and

1. *Initialize*
   Set t=0;
   M : the size of ant colony;
   N : the number of nodes;
   S : the set of source nodes;
   $t_{\max}$: the upper limit of the number of iterations;
   Generate an evacuation network, and the identifiers of generated nodes are recorded in $Table$.
2. *Set all ants at the source nodes*
   For k:=1 to M do
   Put each ant on one random node of the source nodes S;
   Record the identifiers of assigned nodes in $tabu$.
3. *Check the available nodes*
   Check the identifiers in $Table$, and delete the identifiers that appear in $tabu$;
   Output: U is the set of available nodes.
4. *Construct the path.*
   For k:=1 to M do
   Move to next node j with the probability P_{ij}^{k} given by Equation (8);
   Insert the node j in $tabu$.
5. *Evaluate the solution*
   Evaluate the solution according to Equations (1-2).
6. *Update the pheromone*
   For link ij do
   Update the pheromone $\tau_{ij}(t+1)$ given by Equations (9-10);
   Set t:=t+1.
7. *Check stop time*
   If $t < t_{\max}$
   Go to step 2
   else
   Stop
8. *END*

Fig. 2. The ACO based algorithm for evacuation path planning.

$$q_j = \left(\begin{array}{c|c|c|c} \alpha_1 & \alpha_2 & \cdots & \alpha_n \\ \beta_1 & \beta_2 & & \beta_n \end{array}\right) \tag{11}$$

where n is the number of Q-bits, and $|\alpha_i|^2 + |\beta_i|^2 = 1$, $i = 1, 2, \ldots n$.

Such individual with n Q-bits can express 2^n states, for instance, a quantum individual with three Q-bits

$$\left(\begin{array}{c|c|c} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & \frac{1}{2} \\ \frac{1}{\sqrt{2}} & \frac{-1}{\sqrt{2}} & \frac{\sqrt{3}}{2} \end{array}\right) \tag{12}$$

can be represented as

$$\frac{1}{4}|000\rangle + \frac{\sqrt{3}}{4}|001\rangle - \frac{1}{4}|010\rangle - \frac{\sqrt{3}}{4}|011\rangle + \frac{1}{4}|100\rangle + \frac{\sqrt{3}}{4}|101\rangle - \frac{1}{4}|110\rangle - \frac{\sqrt{3}}{4}|111\rangle. \tag{13}$$

It means that the probabilities of the states $|000\rangle$, $|001\rangle$, $|010\rangle$, $|011\rangle$, $|100\rangle$, $|101\rangle$, $|110\rangle$ and $|111\rangle$ are 1/16, 3/16, 1/16, 3/16, 1/16, 3/16, 1/16, and 3/16, respectively [35].

In order to evaluate the performance and fitness of each individual, it is necessary to represent the corresponding solutions in the conventional form. A conventional binary solution can be obtained through observing the Q-bits. For instance, assuming that $x_i (i = 1, 2, \ldots, n)$ represents a bit of the binary individual x, a random number w is generated between [0,1] and compared with α_i of the Q-bit individual, if $|\alpha_i|^2 > w$, then set x_i = "0", otherwise set x_i = "1".

Accordingly, a probable solution P can be obtained through measurement of Matrix Q. Given that $P = (p_1, p_2, \ldots, p_j, \ldots, p_m)$, $p_j (j = 1, 2, \ldots, m)$ is a binary individual with length of n. Every element in p_j (for example, p_{ji}) is determined by comparing α_{ji} of q_j with w, $0 < w < 1$.

The quantum rotation gate is significantly important for the convergence of Q-bit individual to an ideal state. Therefore, the rule of rotation is used to update the Q-bit individual in this paper. The process is introduced in detail in the following Eqs. (14)–(16).

Given that $[\alpha_{ji}, \beta_{ji}]^T$, i.e., the ith bit of the jth individual q_j of solution Q, evolves to $[\alpha'_{ji}, \beta'_{ji}]^T$:

$$\begin{bmatrix} \alpha'_{ji} \\ \beta'_{ji} \end{bmatrix} = G \begin{bmatrix} \alpha_{ji} \\ \beta_{ji} \end{bmatrix} \tag{14}$$

$$G = \begin{bmatrix} \cos\theta_{ji} & -\sin\theta_{ji} \\ \sin\theta_{ji} & \cos\theta_{ji} \end{bmatrix} \tag{15}$$

the rotation angle is generally defined as:

$$\theta_{ji} = \Delta\theta_{ji} \cdot s(\alpha_{ji}, \beta_{ji}) \tag{16}$$

where G represents the quantum rotation gate, $s(\alpha_{ji}, \beta_{ji})$ represents the sign of θ_{ji} that controls the direction, and $\Delta\theta_{ji}$ signifies the magnitude of rotation angle.

Fig. 3 depicts the polar plot of the rotation gate for Q-bit individual. The parameters used to calculate the rotation angle are shown in Table 1, which lists all possible solutions. $f(\cdot)$ represents the fitness function; x_{ji} represents the ith bit of the jth individual of current solution; and b_i represents the ith bit of the best solution b.

4.2.2. QACA based path planning

In this subsection, an improved quantum ant colony algorithm for evacuation path optimization is elaborated.

As an evolutionary algorithm, QACA is a convergence of ACO and QEA, where the pheromone is represented with Q-bit. The evolution of QACA is an adaptive iterative optimization process, since the movement of Q-bit individual applies the random-proportional rule (see (8)) which is in accordance with ACO. In addition, the quantum gate operation ensures that the individual approaches gradually to the searched optimum location.

The computation method of the rotation angle of QACA, i.e., θ_i, differs from that of QEA, and the main difference is caused by $\Delta\theta$, which is a variable related to iteration times. It determines the

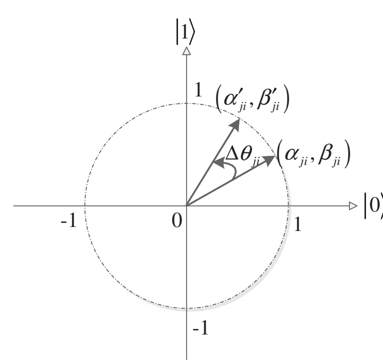


Fig. 3. The polar plot of the rotate gate for Q-bit individual [12].

Table 1
Look-up table of rotation angle of QEA [36].

x_{ji}	b_i	$f(x) > f(b)$	$\Delta\theta_{ji}$	$s(\alpha_{ji}, \beta_{ji})$			
				$\alpha_{ji}\beta_{ji} > 0$	$\alpha_{ji}\beta_{ji} < 0$	$\alpha_{ji} = 0$	$\beta_{ji} = 0$
0	0	False	0	0	0	0	0
0	0	True	0	0	0	0	0
0	1	False	0	0	0	0	0
0	1	True	0.05π	+1	−1	0	±1
1	0	False	0.01π	+1	−1	0	±1
1	0	True	0.025π	−1	+1	±1	0
1	1	False	0.005π	−1	+1	±1	0
1	1	True	0.025π	−1	+1	±1	0

Notes: $f(\cdot)$ represents the fitness function, $s(\alpha_{ji}, \beta_{ji})$ represents the sign of θ_{ji}, x_{ji} represents the ith bit of the jth individual of current solution, and b_i represents the ith bit of the best solution b.

value of rotation angle, convergence rate and performance. The usual computation method of $\Delta\theta$ is to construct a query table (for example, Table 1), while the definition of $\Delta\theta$ adopted in this paper is a dynamic adjustment strategy [37].

$$\Delta\theta = 0.5 * \pi * \exp(-t/t_{\max}) \tag{17}$$

where π is the circumferential ratio; t represents the current iterations; $t_{\max}$ represents the upper limit of iterations.

Assuming that if $s(\alpha_i, \beta_i) > 0$, the rotation gate rotates anticlockwise; if $s(\alpha_i, \beta_i) < 0$, the rotation gate rotates clockwise. Given $Q = (q_1, q_2, \ldots, q_j, \ldots q_m)$, and the population size is m. The updating process of quantum rotation gate is shown as:

$$q_j^{t+1} = G(t) \cdot q_j^t \tag{18}$$

where t represents the iterations; $G(t)$ represents the rotation gate of the t^{th} iteration (see (14) and (15)); q_j^t is the jth individual's probability amplitude of the tth iteration; q_j^{t+1} is the jth individual's probability amplitude of the $(t+1)$th iteration.

The mutation operation can be performed to avoid premature convergence and increase diversity of population. First, choose several ants, and then the quantum non-gate is realized to some Q-bits of the selected individuals with a certain probability [39] (usually [0.01,0.05]). Since a Q-bit is represented by the vector $[\alpha_i, \beta_i]^T$, we can also use the $[\cos\varphi, \sin\varphi]^T$ to express the Q-bit. The mutation process can be described as follows:

$$\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} \cos\varphi \\ \sin\varphi \end{bmatrix} = \begin{bmatrix} \sin\varphi \\ \cos\varphi \end{bmatrix} \tag{19}$$

where φ is mutated to $\pi/2 - \varphi$, namely the phase of Q-bit transformed.

The flowchart of QACA based path optimization approach is shown in Fig. 4. The main steps are discussed below.

Step 1: Initialize $Q(t)$, whose population size is m, i.e., $Q(t) = (q_1^t, q_2^t, \ldots, q_m^t)$.
$q_j^t (j = 1, 2, \ldots, m)$ is the jth individual of the tth iteration, and it is given by

$$q_j^t = \left(\begin{array}{c|c|c|c} \alpha_{j1}^t & \alpha_{j2}^t & \cdots & \alpha_{jn}^t \\ \beta_{j1}^t & \beta_{j2}^t & & \beta_{jn}^t \end{array} \right) \tag{20}$$

where the amount of Q-bits is n, initialize $\alpha_i, \beta_i (i = 1, 2, \ldots, n)$ with $1/\sqrt{2}$ at the beginning. The initial value of iterations is set as $t = 0$, and the maximum value of iterations is defined as t_{max}.

Step 2: Construct $P(t)$ by observing the states of $Q(t)$.
Given that $P(t) = (p_1^t, p_2^t, \ldots, p_j^t, \ldots, p_m^t)$, $p_j^t (j = 1, 2, \ldots, m)$ is a binary individual with length of n. Every element in p_j^t (for example, p_{ji}^t) is determined by comparing α_{ji}^t of q_j^t with w, $0 < w < 1$.

Step 3: Build path. Put m individuals into one of the source nodes randomly. Construct path by using the state transition rules shown in Eqs. (8)–(10) repeatedly.

Step 4: Mutation operation. Select some individuals (10% of the population size), and realize the operation according to Eq. (19).

Step 5: Evaluate $P(t)$. Eq. (7) is the evaluation function. Store the best solution among $P(t)$ into $B(t)$.

Step 6: Update $Q(t)$ according to the quantum rotation rules described in Eq. (18). Set $t = t + 1$.

Step 7: Return to Step 3 till the current iterations exceed maximum number of iterations.

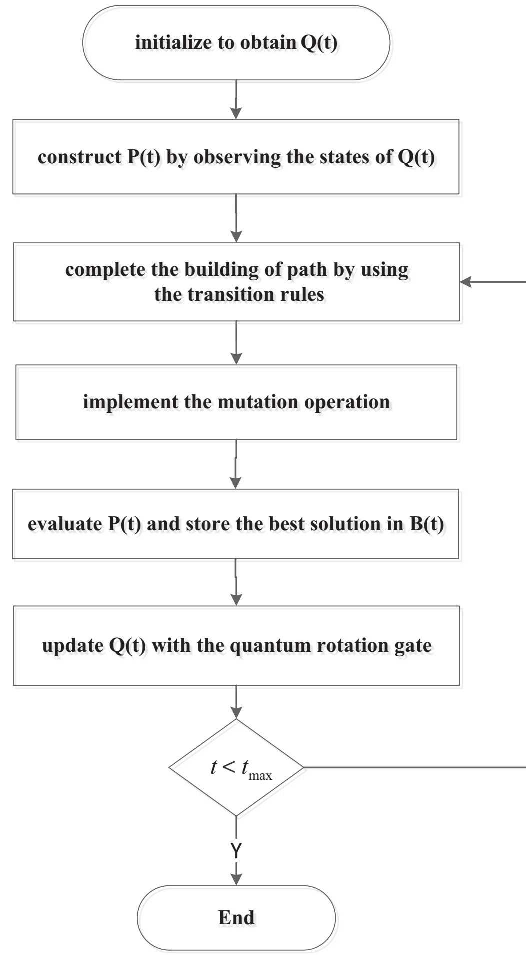


Fig. 4. The flowchart of QACA based optimization method.

5. Case studies and experiment results

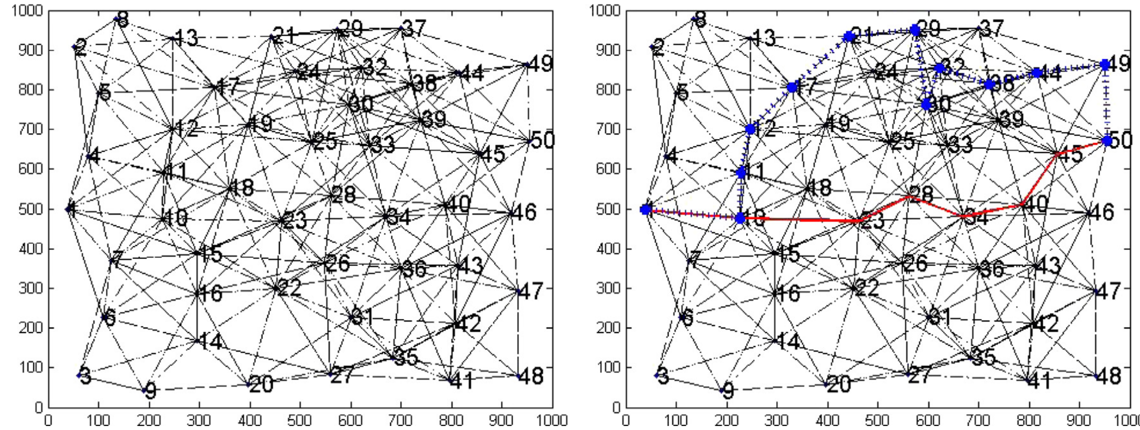
This section is organized into two subsections, both related to the use of QACA to validate its effectiveness and efficiency. The first subsection focuses on comparison of algorithm performances between classic QEA and QACA with three benchmark functions adopted. The second subsection deals with evacuation optimization and makes a comparison of ACO based and QACA based solutions. All the case studies were run on an Intel Core i3 PC of 3.10 GHz and 4 GB RAM.

Table 2
Experiment results of QEA vs. QACA.

Function	Optimal value	QEA			QACA		
		Rate	T	Av	Rate	T	Av
F_1	0	1	40	0	1	51	0
F_2	0	0.37	423	0.0077	0.98	513	1.15E−6
F_3	1	1	61	1	1	25	1

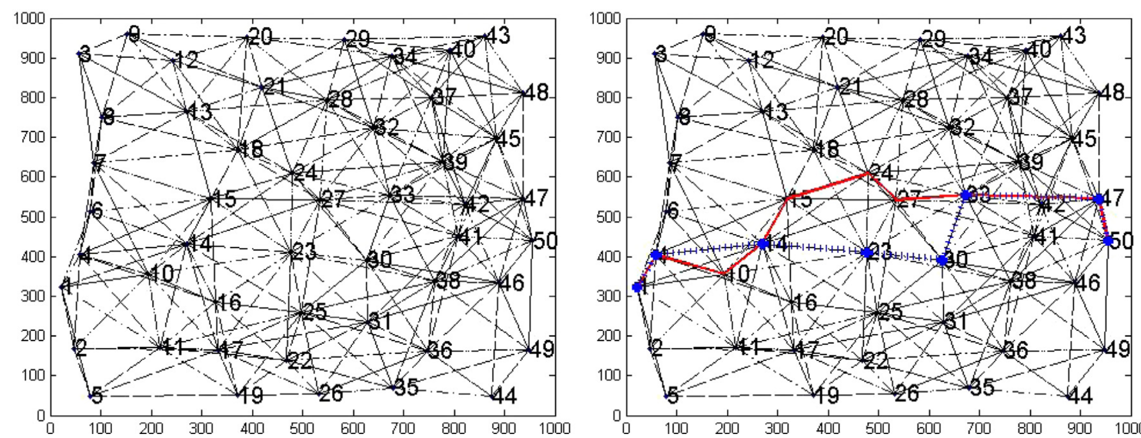
5.1. Numerical experiment

For a comparison, performance indicators [35] including the success rate of finding optimal value (rate), the average iterations to find optimal value (T) and the average optimal value (Av), are introduced to evaluate the optimization ability of the improved



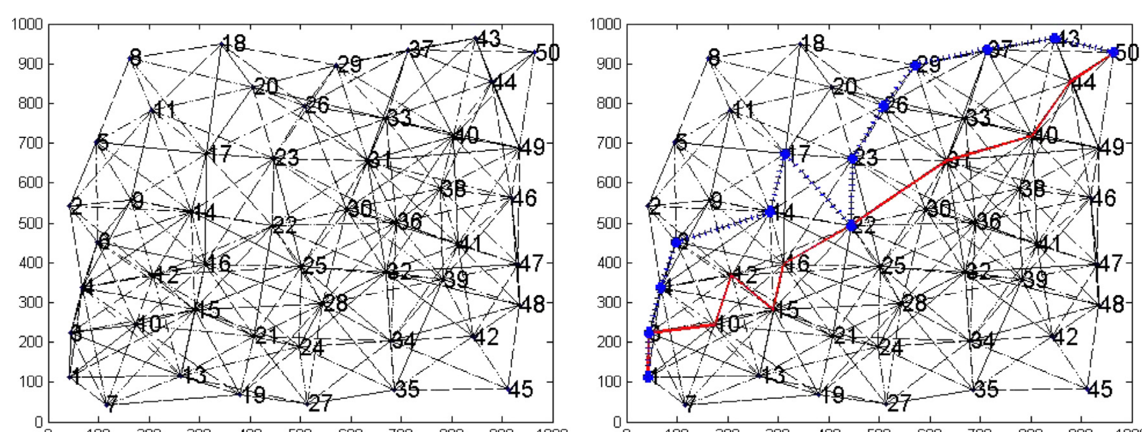
(a) The initial evacuation network. (b) The diagram of optimum path.

Fig. 5. The evacuation network with n = 50, m = 10, t_{max} = 300.



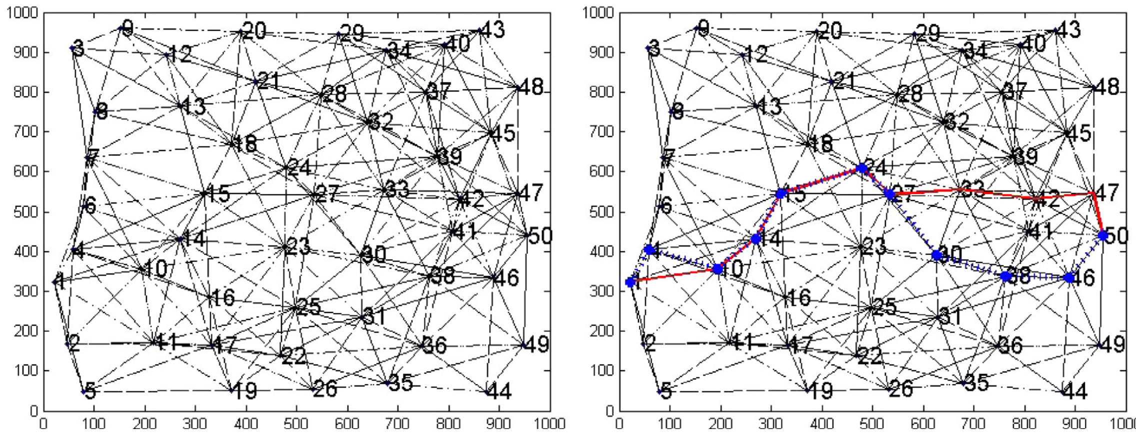
(a) The initial evacuation network. (b) The diagram of optimum path.

Fig. 6. The evacuation network with n = 50, m = 20, t_{max} = 300.



(a) The initial evacuation network. (b) The diagram of optimum path.

Fig. 7. The evacuation network with n = 50, m = 30, t_{max} = 300.



(a) The initial evacuation network. (b) The diagram of optimum path.

Fig. 8. The evacuation network with $n = 50$, $m = 40$, $t_{\max} = 300$.

Table 3
Comparison between ACO and QACA by evacuation case when $n = 50$ and $m = 10$.

		$t_{\max}$					
		50	100	150	200	300	400
l_{opt} (m)	ACO	2557	2609	2834	1952	2613	2435
	QACA	2611	2589	2950	1897	1970	1971
Et (s)	ACO	40,546	56,383	53,073	50,469	49,196	54,416
	QACA	42,814	40,356	47,828	35,209	41,948	42,798

Table 4
Comparison between ACO and QACA by evacuation case when $n = 50$ and $m = 20$.

		$t_{\max}$					
		50	100	150	200	300	400
l_{opt} (m)	ACO	2188	3982	1881	2177	2429	1948
	QACA	2355	3269	2025	2377	2275	1901
Et (s)	ACO	120,654	132,934	77,393	83,454	118,942	94,805
	QACA	122,830	114,424	72,239	80,812	106,687	81,872

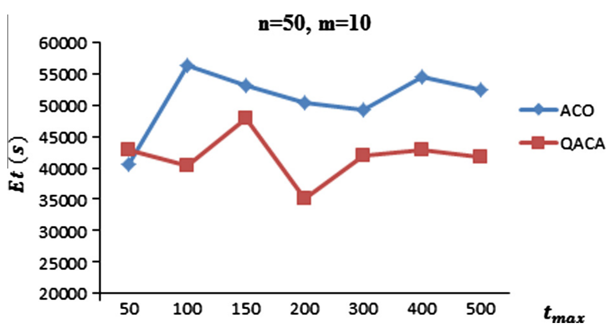


Fig. 9. Tendency chart of Et with $n = 50$ and $m = 10$.

QACA, and the benchmark functions used in this experiment are listed as follows:

$$F_1 = (x_1^2 + x_2^2)^{0.25}\left[\sin^2(50(x_1^2 + x_2^2)^{0.1}) + 1.0\right], \quad -100 < x_i < 100 \tag{21}$$

$$F_2 = [-13 + x_1 + ((5 - x_2) \cdot x_2 - 2) \cdot x_2]^2 + [-29 + x_1 + ((x_2 + 1) \cdot x_2 - 14) \cdot x_2^2]^2, \quad -10 \leqslant x_i \leqslant 10 \tag{22}$$

$$F_3 = 0.5 - \frac{\sin^2\sqrt{x_1^2 + x_2^2} - 0.5}{(1 + 0.001(x_1^2 + x_2^2))^4}, \quad -100 < x_i < 100 \tag{23}$$

where F_3 has the global maximum, others have the global minimum.

In this experiment, the population size was 20, and the length of the Q-bit was 30 bits. The experiment was repeated for 100 runs, and the fixed maximum generation was 1000.

Table 2 describes the experiment results. It can be noted from Table 2 that QEA performed slightly better than QACA in terms of average iterations for F_1. As to F_2, in spite of 90 iterations greater than QEA, QACA performance better in respect of success rate, which is more than twice as much as that of QEA. Furthermore, the average optimal value of QACA is correct to six decimal places, which is two decimal places better than $A\upsilon$ of QEA. For F_3, QACA is obviously superior to the classic QEA in respect of time efficiency. In general, the QACA has a better accuracy, while the advantage of QACA is not so evident in dealing with simple optimization problems.

5.2. Case studies

In this subsection, a random network typology is generated to represent the evacuation network, and MATLAB 2012b is used as the simulation platform.

Each individual is taken as an evacuee in this case. Figs. 5–8 describe different evacuation situations with various conditions, such as the size of population m and the maximum number of iterations. Fig. 5(a) shows an instance of such a network with 50 nodes, and the area of evacuation zone is 1 square kilometer. Each link of two accessible neighbor nodes is connected by a straight dotted line. Assume that both the set of source nodes and the set of destination nodes contain one element, and the movement speed of each evacuee is a constant, i.e., 2 m/s. Thus, the evacuation problem in this task is to evacuate people in Node 1 to Node 50.

Due to the randomness of the generated network, the initial evacuation networks have dissimilar typologies. Correspondingly, the evacuation path varies with the typology, as illustrated in Figs. 5–8. The red solid line signifies the optimum path sought out by QACA based solution, while the blue dotted line with plus sign represents the optimum path searched out by ACO based solution.

Two indicators, i.e., l_{opt} and Et, were chosen to compare ACO based and QACA based solutions with different values of $t_{\max}$. l_{opt} denotes the length of the optimum path, as a non-global

Table 5
Comparison between ACO and QACA by evacuation case when $n = 50$ and $m = 30$.

		t_{max}					
		50	100	150	200	300	400
l_{opt} (m)	ACO	2935	2421	2354	2239	2099	2170
	QACA	2684	2402	2217	2049	2020	2018
Et (s)	ACO	144,131	187,351	159,894	149,427	111,605	147,879
	QACA	142,765	173,114	149,627	136,569	105,321	130,366

Table 6
Comparison between ACO and QACA by evacuation case when $n = 50$ and $m = 40$.

		t_{max}					
		50	100	150	200	300	400
l_{opt} (m)	ACO	2430	1918	2276	2301	2234	2544
	QACA	2214	1928	2151	2130	2118	2281
Et (s)	ACO	179,373	207,967	137,620	194,824	161,437	233,948
	QACA	174,920	185,890	119,626	185,218	146,601	220,569

measurable indicator, reflects the local performance of solution to some extent. Et represents the total evacuation time of all individuals to find the optimum path during the iteration. Therefore, the smaller the value of Et is, the better the effectiveness and efficiency of solution is.

Table 3 shows the results of l_{opt} and Et under six scenarios that t_{max} values 50, 100, 150, 200, 300 and 400 respectively. It can be seen from Table 3 that QACA based solution shows a little advantage on condition that the number of iterations is small, especially when $t_{max} = 50$, the value of Et acquired by ACO based solution is smaller than that of QACA based solution. As t_{max} increases, the superiority of the proposed solution comes to be more obvious.

The tendency of Et with different iterations when $n = 50$ and $m = 10$ is displayed in Fig. 9. The x-axis denotes the maximum number of iterations, i.e., t_{max}, while the y-axis represents the total evacuation time, i.e., Et. We can see from Fig. 9 that the value of total evacuation time for QACA based solution is generally less than the same value for ACO based solution except when the value of t_{max} is 50. The line of QACA starts to maintain level when t_{max} values 300.

Tables 4–6 list the results of l_{opt} and Et when the size of population m is 20, 30 and 40 respectively. Overall, the performance of QACA based solution is better than that of ACO based solution. The difference is small when the number of iterations is small. But as the number increases, the growing superiority of the proposed solution in time efficiency reveals gradually. Since the network topology is not fixed, the value of optimum evacuation time has a slight fluctuation.

6. Conclusion

Evacuation planning covers more than a few decisions which have to be made in a very short time and in the most appropriate way. This paper proposes a QACA based evacuation optimization approach. Basic concepts and principles of QEA are introduced into ACO based optimization method, therefore, it is expected to avoid slow convergence and improve efficiency. Simulation results by comparing ACO based and QACA based solutions show that QACA is efficient in solving this problem, and the advantage of QACA based solution tends to expand as the number of iterations increases. Besides, it should be noticed that the research focus is not confined to a single path between two locations (origin–destination), and the proposed method is suitable for multiple source nodes to multiple destination nodes.

In our future work, improvements are possible in multiple aspects. Relevant context variables affecting the evacuation process should be taken into account. Factors like network dynamics and human behaviors have significant effects on evacuation optimization and should be considered. Furthermore, the advancements of mobile communication networks and wireless sensor networks make it much easier to obtain real data of evacuation zones and evacuees instantly. These technologies also promote some other future research directions.

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