Journal of Intelligent & Fuzzy Systems 28 (2015) 107–116
DOI:10.3233/IFS-141280
IOS Press

Vehicle route assignment optimization for emergency evacuation in a complex network[1]

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Abstract. Most traffic delays during regional evacuations occur due to a large number of vehicles are grouped for a short time. Thus, the reasonable assignment of a vehicle route is one strategy for reducing these delays. To identify an optimal vehicle route assignment plan, this paper presents a multi-source and multi-destination traffic network model. This model is an extension of the minimum cost flow problem and it improves the definition of the travel time based on the traffic volume. It can be used to formulate vehicle routing plans that alleviate traffic congestion and reduce the evacuation time. A genetic algorithm is modified to find the solution for this model. The solution trades off the total vehicle travel distance against traffic jams. An application is presented for Wenzhou city, Zhejiang province, China.

Keywords: Emergency evacuation, vehicle route assignment, genetic algorithm

1. Introduction

As economies develop, urban population increases and road networks become denser in many larger cities. Traffic congestion occurs frequently. During emergency management after many hazardous events, the best option is to relocate threatened populations to a safer area. If large-scale evacuations are implemented, most people will drive to the safe areas, so a large number of vehicles enter the traffic network in a short time, which can easily cause traffic gridlock. In 2005, the American government ordered an evacuation before Hurricane Rita arrived, but the vehicles caused traffic congestion because of the lack of an evacuation plan [1]. Thus, assigning a vehicle evacuation route to ensure safe and rapid evacuations is an urgent and practical problem.

In previous studies of emergency vehicle evacuations, the definition of the traffic network is the foundation of modeling. Most researchers set the evacuation source and shelter at ends of the network, such as the cell transmission model (CTM) built by Chiu and Zheng [2], which was also built by Zhang and Chen [3], and the multi-object evacuation network model built by Stepanov and Smith [4]. These models only need to consider the evacuation of vehicles from one side to the other in the network, which is too simple to represent the actual situation. The density of people and the road network is very high in China and most of the residential areas are in the city center, which means evacuation points may be in the center of the network rather than at one end, so the locations of evacuations and the destinations used in the models mentioned above are unrealistic.

Many researchers use maximum flow models or minimum cost flow models to design evacuation programs to maximize the flow between the source and destination via a capacitated network. Dunn and Newton [5] proposed a maximum flow model to program evacuation routing. Cova and Johnson [6] proposed a

[1]Supported by the National Natural Science Foundation of China (NSFC: 41001358, 41471424).

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minimum cost flow model via a capacitated network to find the minimum total travel distance without merging. Although these models can avoid traffic congestion and minimize the total travel distance, they do not consider the vehicle speed and travel time because of the characteristics of the models. Thus, the travel time is treated as an objective function, or less often as a decision variable, and the optimal models cannot ensure that the total travel time is minimum. However, some researchers have introduced the travel time in their models. Gao and He [7] used the intersection delay as the node weight and travel time as edge weight, before building a minimum cost flow model to minimize the total weight. The optimal objective of this model included the travel time, but it was assumed to be used as a known condition rather than obtained by calculation, which could not solve practical problems.

Some researchers have used traffic flow theory to produce models. Based on the theoretical cell transmission model (CTM) proposed by Daganzo [8], Liu et al. [9] and Xie et al. [10] build two-level optimization network models based on CTM, which were used as lower level models to minimize the evacuation time. The upper level model built by Liu et al. [9] was used to maximize the flow in the network, while Xie et al. [10] built a high-rise model to optimize the network evacuation process using lane-reversal and crossing-elimination constraints. Chiu and Zheng [2] designed a real-time emergency response evacuation model for multi-priority groups, which used a CTM based on the node traffic network. The aim of the model was to minimize the travel time to provide a departure schedule for victims and response groups. All of these models provided methods for calculating the travel time based on the theory of traffic flow, although the computational expressions had different forms, which had to be solved by simulation. Thus, the CTM model has certain limitations. Yuan and Wang [11] stated that the evacuation time is determined by the travel speed and distance, where the speed is variable when the disaster spreads. The optimal aim of their model was to minimize the total evacuation time. Although the model defined a computational expression for the travel time, the attenuation coefficient for speed needed to be explicit for the calculated time period, which had relationships with the distance to the disaster sources, the vulnerability of the arc, the type of disaster, etc. Thus, the value of the attenuation coefficient was somewhat arbitrary.

By studying the total evacuation time as the optimal object or decision variable in a model, Zhang et al. [12] proposed a multi-source model to minimize the total evacuation time for all evacuees by considering the priority of evacuation. Song et al. [13] built a location routing model using buses for evacuation. This model considered the uncertain demands of the bus station, where the objective function was minimizing the total travel time of the arc in the network. The minimum evacuation time was optimized in these models but the travel time of arcs was assumed to be known before the calculations, so the models lacked operability in practical applications.

In addition, some researchers used the minimum evacuation distance as the optimal objective. The multi-object optimization model built by Saadtseresht and Mansourian [14] selected the safe areas as shelter firstly and then searched for the best routes between the evacuation sources and shelters to ensure that the total distance was minimized. The weak point of this model was that the vehicle flow attribute was not considered because the distance of some arcs in the network was not the shortest, although the travel time may have been the shortest due to the different number of lanes. Therefore, using the evacuation distance as the optimal objective rather than the evacuation time cannot solve the Vehicle Route Assignment (VRA) Problem.

This paper presents a more realistic network flow model which has multi-sources and multi-destinations, in the network those sources nodes are intermediate nodes simultaneously. The model is in accordance with the actual cases of densely populated cities. And then, the travel time for a vehicle passing arcs is calculated on the basis of queuing theory, the method avoids complex of CTM and roughness of maximal flow model. According to the model's feature, a modified genetic algorithm (GA) is built up to find the optimization solution of this model.

This paper is organized as follows. The background and literature review are presented in Section 1 and a network model for evacuation planning with vehicles is described in Section 2. A modified GA-based model is explained in Section 3 to solve the VRA problem. In Section 4, a practical application set in Wenzhou demonstrates the solution procedure for the model and algorithm. Conclusions and further research are summarized in Section 5.

2. Problem definition and the main assumptions

In general, vehicles are evacuating from many evacuation sources (such as districts) to multi-shelters. The evacuation routes are intersecting and complex, and

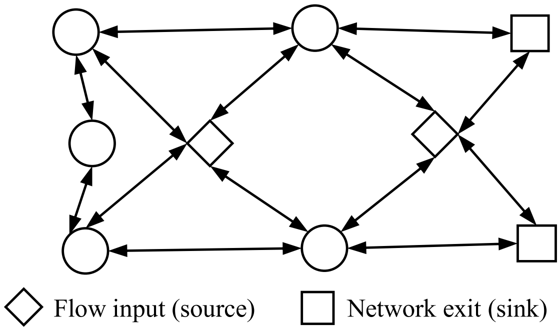

Fig. 1. The structure of evacuation network.

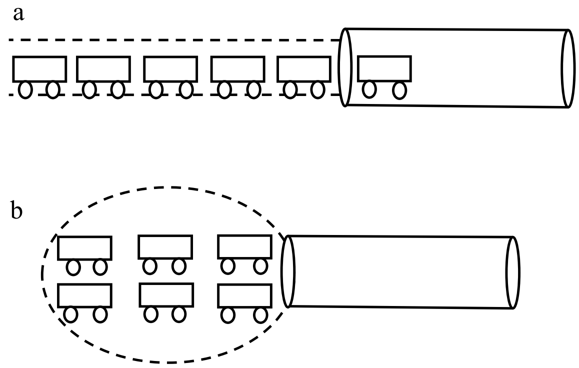

Fig. 2. The travel logic for vehicles. a) Vehicles passing the arc one by one. b) The vehicles gather at the starting node and wait.

intermediate nodes of the traffic network also need to evacuate residents. This is why many sources and intermediate nodes are coincident so it is difficult to divide at the evacuation network level. So, this paper put forward a multi-sources and multi-destinations network, in which the evacuation sources and general nodes are mixed. Figure 1 shows the evacuation network.

We define a directed graph $D(V, A)$ with node set V and arc set A. The nodes are of three types: source node V_O, intersection node V_I, and sink node V_D, which can be specified as follows:

- i index of network nodes
- $i \longrightarrow j$ directed arc from node i to node j
- L_{ij} distance along $i \longrightarrow j$
- S_{ij} set limited travel speed on $i \longrightarrow j$
- Q_{ij} limited traffic flow on $i \longrightarrow j$, i.e., the number of vehicles that pass along the arc per hour

[The value of parameters Q_{ij} and S_{ij} are based on Design Specification for Highway Route (JTG D20-2006).]

- t_{ij} the vehicle travel time along $i \longrightarrow j$
- D number of shelters V_d
- O number of evacuation sources V_o
- E_o total number of vehicles that need to be evacuated from source node V_o

2.1. Definition of the travel time based on a discretized queuing model

In traditional minimum cost flow models, the travel time on an arc is generally assumed to be a constant as the weight of arc. This can also be calculated using a flow-density model [15] where the expression is a complex nonlinear function. The former is too simple and crude, because it cannot express the time delay caused by traffic congestion whereas the latter is difficult to model and to obtain a numerical solution.

In order to reflect the relationship between traffic volume and travel time, this paper presents a calculation method of travel time on the basis of queuing model. The movements of vehicles can be described as queuing model, which are divided into two processes: the vehicles f_{ij} that need to pass arc (v_i, v_j) collect at the starting node; and then the vehicles f_{ij} pass this arc one by one after all the vehicles have arrived. The vehicles wait at the end node to pass the next arc until all of the vehicles have passed this arc (Fig. 2). Although this assumption is not consistent with reality and it amplifies the travel time, the changing trend between the travel time and arc flow reflected by the assumption is consistent with reality, which can guarantee the effectiveness of the solution during optimization.

Thus, the vehicle travel time along $i \longrightarrow j$ tij is equal to the sum of the waiting time and the driving time. The driving time represents the time that the first vehicle passes the arc $i \longrightarrow j$, which is equal to L_{ij}/S_{ij}; The waiting time represents the time that the last vehicle queues in line. When the arc flow Q_{ij} is constant, the waiting time is f_{ij}/Q_{ij}. Thus, the expression of the travel time t_{ij} is:

$$t_{ij} = f_{ij}/Q_{ij} + L_{ij}/S_{ij} \tag{1}$$

2.2. Model formulation

VRA optimization can be defined as follows:

Decision variables:

y_{ij}^{n} 1 if vehicle n in arc $i \longrightarrow j$, 0 if vehicle m in arc $i \longrightarrow j$,

f_{ij} number of vehicles travelling along $i \longrightarrow j$ (net flow from node i to node j), $f_{ij} = \sum_m y_{ij}^m$.

$$\text{Minimize: max} \left\{ \sum_i \sum_j y_{ij}^n \, t_{ij}^n \right\} \quad (2)$$

$$\text{Subject to: } t_{ij} = \frac{f_{ij}}{Q_{ij}} + \frac{L_{ij}}{S_{ij}}, \ \ (\upsilon_i, \ \upsilon_j) \in A \quad (3)$$

$$\sum\nolimits_{i:(i,\ j)\in A} f_{ij} - \sum\nolimits_{j:(j,\ i)\in A} f_{ji} = 0, \ i \neq o, \ i \neq d \quad (4)$$

$$\sum\nolimits_{(o,\ j)\in A} f_{oj} - \sum\nolimits_{(j,\ o)\in A} f_{jo} = E_o \quad (5)$$

$$\sum\nolimits_d \sum\nolimits_{(d,\ j)\in A} f_{dj} - \sum\nolimits_d \sum\nolimits_{(j,\ d)\in A} f_{jd} = -\sum\nolimits_o E_o \quad (6)$$

$$y_{ij}^n = 0 \ or \ 1, \ \ f_{ij} \geq 0 \ and \ \text{int}, \ \ for \ all \ i \rightarrow j \quad (7)$$

The objective function (2) aims to minimize the maximum travel time. Constraint (4) is the standard flow conservation constraint in a network flow problem: the flow out of a node minus the flow into the node must be equal to the net flow at the node. Constraint (5) guarantees that the difference between the outflow and inflow of the source node is equal to the vehicles that need to be evacuated to this node. Constraint (6) guarantees that the sum of the difference between the outflow and inflow at the destination nodes is equal to the total vehicles that need to be evacuated from all sources.

2.3. *Initialization of the evacuation route*

When the number of nodes is n and the number of vehicles is m in the problem above, the computational complexity is O(n^{nm}). The number of optional routes from one evacuation source to the shelter grows exponentially in this model, which is difficult to calculate. In order to reduce computational complexity and to be consistent with the reality, we use the K-shortest paths [16] algorithm to find K routes, which are the shortest from V_o to V_d.

The parameters that determinate the evacuation time in this model are the distance L_{ij} and the limited flow Q_{ij} of arcs, so we choose L_{ij}/Q_{ij} (the ratio of distance and limited flow) as the weight of arc $i \longrightarrow j$ to search for the shortest path. After all of the evacuation routes have been initialized, the parameters can be defined as follows:

Matrix $R_{od}^{(k)}$ the k-th shortest evacuation route from V_o to V_d

r_{ij} 1 if arc $i \longrightarrow j$ is in route $R_{od}^{(k)}$, and 0 otherwise

$$R_{od}^{(k)} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nn} \end{bmatrix}$$

$T_{od}^{(k)}$ evacuation time of k-th route from V_o to V_d

$L_{od}^{(k)}$ distance of k-th route from V_o to V_d

Matrix F the number of vehicles travelling in network

f_{ij} represents the total vehicles on the evacuation routes that contain the arc $i \longrightarrow j$.

$$F = \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1n} \\ f_{21} & f_{22} & \cdots & f_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ f_{n1} & f_{n2} & \cdots & f_{nn} \end{bmatrix}$$

The decision variables can be revised as:

$x_{od}^{(k)}$ number of vehicles travelling along route $R_{od}^{(k)}$

The traffic network model for the VRA problem is formulated as:

$$\text{Minimize: max} \left\{ T_{od}^{(k)} \right\}, \ \forall o, \ \forall d, \ \forall k \quad (8)$$

The objective function (8) aims to minimize the maximum evacuation time of all routes $R_{od}^{(k)}$. Where $T_{od}^{(k)}$ can be calculated as follows:

$$T_{od}^{(k)} = \sum\nolimits_i \sum\nolimits_j r_{ij} t_{ij}, \ \ r_{ij} \in R_{od}^{(k)} \quad (9)$$

$$t_{ij} = \frac{f_{ij}}{Q_{ij}} + \frac{L_{ij}}{S_{ij}}, \ \ (\upsilon_i, \ \upsilon_j) \in A \quad (10)$$

$$F = \sum\nolimits_d \sum\nolimits_o \sum\nolimits_k R_{od}^{(k)} x_{od}^{(k)} \quad (11)$$

In matrix F, f_{ij} is also determined by $R_{od}^{(k)}$, and it can be calculated if $x_{od}^{(k)}$ is given.

$$L_{od}^{(k)} = \sum\nolimits_i \sum\nolimits_j r_{ij} f_{ij}, \ \ r_{ij} \in R_{od}^{(k)} \quad (12)$$

The constraints can be written as:

$$\sum\nolimits_d \sum\nolimits_k x_{od}^{(k)} = E_o, \ \ \forall_o \quad (13)$$

$$\sum\nolimits_d \sum\nolimits_o \sum\nolimits_k x_{od}^{(k)} = \sum\nolimits_o E_o \quad (14)$$

$$\sum\nolimits_{i:(i,\ j)\in A} f_{ij} - \sum\nolimits_{j:(j,\ i)\in A} f_{ji} = 0,\ i \neq o,\ i \neq d \tag{15}$$

$$\sum\nolimits_{(o,\ j)\in A} f_{oj} - \sum\nolimits_{(j,\ o)\in A} f_{jo} = E_o \tag{16}$$

$$\sum\nolimits_{d}\sum\nolimits_{(d,\ j)\in A} f_{dj} - \sum\nolimits_{d}\sum\nolimits_{(j,\ d)\in A} f_{jd} = -\sum\nolimits_{o} E_o \tag{17}$$

$$x_{od}^{(k)} \geq 0\ and\ \text{int},\ \forall o,\ \forall d,\ \forall k \tag{18}$$

$$f_{ij} \geq 0\ and\ \text{int},\ for\ all\ i \rightarrow j \tag{19}$$

$$r_{ij} \in \{0,\ 1\},\ for\ all\ i \rightarrow j \tag{20}$$

Constraint function (13) guarantees that the sum of vehicles in $R_{od}^{(k)}$ from evacuation source V_o is equal to the vehicles that need to be evacuated from V_o. Constraint function (14) guarantees that the sum of vehicles on all of the evacuation routes is equal to the total vehicles that need to be evacuated from all of the evacuation sources. Constraints (15–17) are the same as Constraints (4–6). Constraints (18–20) define the types for all of the variables.

3. Description of the algorithm

As a solution of the model, the range of the number of vehicles $x_{od}^{(k)}$ is from 0 to E_o, E_o and the total number of evacuation routes from all of the evacuation sources to destination is $K \cdot O \cdot D$. Thus, the size of the solution space is $E_o^{K \cdot O \cdot D}$. This is an NP-hard problem, so the heuristic algorithm can be adopted to solve it. The decision variables are numbers of vehicles travelling along each arcs, it is suitable to be transformed to gene of Genetic Algorithm [17]. However, the operators of traditional GA cannot solve the problem; this paper modifies the process of reproduction, crossover, and mutation to find an effective solution.

3.1. Generation of the initial population

The fitness function h is defined as the reciprocal of the objective function:

$$h = 1\Big/\max\left\{T_{od}^{(k)}\right\},\ \forall V_o,\ \forall V_d,\ \forall k \tag{21}$$

The number of vehicles $x_{od}^{(k)}$ is taken as a gene on chromosome g and all $x_{od}^{(k)}$ on every route $R_{od}^{(k)}$ comprise one chromosome, so the coding of the solution is a natural number and the population size is B.

The routes for each evacuation source node V_o are sorted by the distance $L_{od}^{(k)}$ from short to long and, according to the sequence, we define x_{om} as the number of vehicles travelling along the m-th longest route from the source node V_o, ($m = 1,2,\ldots,M$; $M = k{\cdot}D$ and $N = k{\cdot}O{\cdot}D$). Thus, the chromosome g is as follows:

$$g = \{x_{11},\ x_{12},\ldots\ x_{1M};\ x_{21},\ x_{22},\ \ldots\ x_{2M};\ \ldots;$$
$$x_{o1},\ \ldots\ x_{oM};\ \ldots\ ,x_{o1},\ldots\ x_{oM}\}$$

The method for generating the initial chromosome is as follows:

Step 1. The routes for each evacuation source node V_o are sorted by the distance $L_{od}^{(k)}$ from short to long. Initialize$\bar{E}_o = E_o$, $i = 1$.

Step 2. According to the sequence above, the number of vehicles x_{om} is assigned randomly. The expression of the assignment of x_{om} is:

$$x_{om} = INT\left(RAND\left(0,\ \bar{E}_o\right)\right)$$
$$\bar{E}_o = \bar{E}_o - x_{om}$$

$m = m + 1$

Rand function() denotes taking a random number based on the uniform distribution of the interval of the values in the brackets. *Int* function() denotes rounding values smaller than the value in the bracket.

Step 3. If $m <$ M, go to Step 2; if $m =$ M, $x_{om} = E_o - \sum_{i=1}^{M-1} x_{oi}$, go to Step 4.

Step 4. Repeat Step 2 B times for every source node until the initial population is produced.

3.2. Modified GA

(1) Selection and reproduction rule

Firstly, the chromosomes are sorted by size of fitness h and the firstly quarter of chromosomes in the new sequence is reproduced to yield two copies where the middle chromosomes are kept the same and the latter quarter of the chromosomes are deleted. The process is shown in Fig. 3 [18]. The Roulette rule is used to reproduce the new population [19].

(2) Crossover rule I

The traditional crossover rule is not entirely suitable for this model since the chromosome genes are the evacuation vehicles x_{om} on the routes, which only changes their position rather than their size during the

$$G=\{\overbrace{g_1,g_2,\cdots,g_{B/4}}^{\text{Copy former quarter}},\overbrace{g_{(B/4)+1},g_{(B/4)+2},\cdots,g_{(3B/4)-1},g_{3B/4}}^{\text{Keep middle the same}},\overbrace{g_{(3B/4)+1},\cdots,g_{B-1},g_B,}^{\text{Delete latter quarter}}\}$$

Fig. 3. GA selection rule.

traditional crossover. Thus, a modified crossover is used to redistribute the vehicles x_{om} in the m-th routes of each evacuation source V_0 in order to expand the range of the feasible solutions.

The redistribution rule is as follows:

Firstly, the routes for each evacuation source node V_o are sorted based on the evacuation time $T_{od}^{(k)}$ from long to short. m is used to mark the route according to the sequence, before Tom is marked as the evacuation time of $T_{od}^{(k)}$, and x_{om} can be assigned to correspond to T_{om}. For example, x_{o1} is the number of vehicles travelling along the route of the longest evacuation time T_{o1} from source node V_0, where x_{om} corresponds to the shortest evacuation time T_{om}.

The number of vehicles in the 1-st route where the evacuation time is longest is reduced by the propotion ω. ω is calculated as follows:

$$\omega=\frac{t_{o1}-t_{o2}}{t_{02}} \tag{22}$$

$\Delta\ x_o$ represents the reduction in the number of vehicles in the 1-st route:

$$\Delta\ x_o=\begin{cases}\omega x_{o1}, & \omega<1\\ 0, & \omega\geq 1\end{cases} \tag{23}$$

For example, if $\omega=\frac{160\ minutues-120\ minutues}{120\ minutues}=\frac{1}{3}<1$, then $\Delta\ x_o=\frac{1}{3}x_{o1}$; if $\omega=\frac{250\ minutues-100\ minutues}{100\ minutues}=1.5>1$, then $\Delta\ x_o=0$.

Finally, the reduced number of vehicles $x_{o1}-x_{o1}^*$ are distributed equally to the other routes where the evacuation vehicle is not 0, except the 2-ed route, and the distributed vehicles should be integers. The rest of the reduced vehicles (if any) are distributed to the 2-ed route. The expression of the evacuation vehicles x_{om} for evacuation source V_o after redistribution is as follows:

$$x_{om}=\begin{cases}x_{om}-\Delta\ x_o, & m=1\\ x_{om}+\Delta\ x_o-\alpha\cdot\text{int}\left(\dfrac{\Delta x_o}{\alpha}\right), & m=2\\ x_{om}+\text{int}\left(\dfrac{\Delta x_o}{\alpha}\right), & m\neq 1,\ m\neq 2,\ x_{om}\neq 0\end{cases} \tag{24}$$

α represents the number of routes where the evacuation vehicles are not 0, except the two routes where the evacuation times are the maximum and the second maximum in V_o. The redistribution process is finished when the vehicles from all of the evacuation sources have been redistributed.

(3) Crossover rule II

In the set of chromosomes G, each chromosome is checked firstly in the set of odd number position chromosomes $\{g_1,\ g_3,\ g_5,\ \cdots,\ g_{2n-1}\}$. If the chromosome g_{2n-1} satisfies the crossover probability $P_c^{(2)}$, this chromosome and the neighboring even number chromosome g_{2n} are taken to have been improved.

The rule for improving the chromosome is as follows.

Firstly, an evacuation source Vo is selected randomly according to the uniform distribution in the interval of the evacuation sources set $\{V_1,\ V_2,\ V_3,\cdots,\ V_o\}$. Next, the corresponding vehicles in the first route R_{o1} of this evacuation source are exchanged and the vehicles are completed in the last route R_{om} of this evacuation source. During crossover, the sum of vehicles in all of the routes of evacuation source V_o should be equal to the total vehicles E_o that need to be evacuated from V_o. The crossover process is shown in Fig. 4.

Two new chromosomes are produced after crossover and the changed vehicles are as follows:

$$\begin{aligned}
x_{o1}&=\begin{cases}x'_{o1}, & x_{o1}+x_{oM}-x'_{01}\geq 0\\ x_{o1}+x_{oM}, & x_{o1}+x_{oM}-x'_{o1}<0\end{cases}\\
x_{oM}&=\begin{cases}x_{o1}+x_{oM}-x'_{o1}, & x_{o1}+x_{oM}-x'_{01}\geq 0\\ 0, & x_{o1}+x_{oM}-x'_{o1}<0\end{cases}\\
x'_{o1}&=\begin{cases}x_{o1}, & x'_{o1}+x'_{oM}-x_{01}\geq 0\\ x'_{o1}+x'_{oM}, & x'_{01}+x'_{oM}-x_{01}<0\end{cases}\\
x'_{oM}&=\begin{cases}x'_{o1}+x'_{0M}-x_{o1}, & x'_{o1}+x'_{oM}-x_{01}\geq 0\\ 0, & x'_{01}+x'_{oM}-x_{01}<0\end{cases}
\end{aligned} \tag{25}$$

This crossover process is operated M-1 times beginning from the first route R_{o1} and ending at the second last route $R_{o,M-1}$, so 2(M–1) new chromosomes are produced. The two chromosomes with the maximum fitness are selected as the optimum chromosomes for

$$g_{2n-1} = \{ x_{11}, x_{12}, \dots x_{1M};\ x_{21}, x_{22}, \dots x_{2M};\ \dots; \boxed{x_{o1},} \dots \boxed{x_{oM}}; \dots, x_{O1}, \dots x_{OM}\}$$

$$g_{2n} = \{ x_{11}', x_{12}', \dots x_{1M}';\ x_{21}', x_{22}', \dots x_{2M}';\ \dots; \boxed{x_{o1}'} \dots \boxed{x_{oM}'}; \dots, x_{O1}', \dots x_{OM}'\}$$

Fig. 4. Crossover of chromosome.

improvement and the two former chromosomes g_{2n-1} and g_{2n} are replaced with them [20].

(4) Mutation rule

Firstly, a random integer $m^{'}$ is produced according to the uniform distribution in the interval from 0 to M. According to the serial number $m^{'}$, the evacuation source V_o that includes the route $R_{om'}$ can be found. Next, the vehicles $x_{om'}$ in route $R_{om'}$ are reduced to 0. The reduced vehicles are distributed equally to the routes where the vehicles are not 0 and the distributed vehicles should be integers. Finally, the remaining vehicles are returned to route R_{om}. The expression for the new vehicles after mutation is:

$$x_{om} = \begin{cases} x_{om} + \mathrm{int}\left(\dfrac{x_{om'}}{\alpha}\right), & x_{om} \neq 0,\ m \neq m^{'} \\ x_{om} - \alpha \cdot \mathrm{int}\left(\dfrac{x_{om'}}{\alpha}\right), & m = m^{'} \end{cases} \tag{26}$$

where α represents the number of routes where the evacuation vehicles are not 0.

Modified GA procedure

The modified GA procedure can be summarized as follows.

Step 1. Set the value of the probability of crossover $P_c^{(1)}$, the probability of crossover $P_c^{(2)}$, the probability of mutation Pm, and the maximum iteration times Tmax. Generate chromosomes G where the population size is B. Set the value of the initial iteration times $T = 0$

Step 2. Calculate the fitness h of each chromosome g and apply the reproduction process to the set of chromosomes G. Obtain a new set G_1.

Step 3. Apply the crossover process to set G_1 according to the probability of crossover $P_c^{(1)}$. Obtain a new set G_2.

Step 4. Apply the crossover process to set G_2 according to the probability of crossover $P_c^{(2)}$. Obtain a new set G_3.

Step 5. Apply the mutation process to set G_3 according to the probability of mutation P_{m}. Obtain a new set G_4.

Step 6. Set $T = T + 1$. If $T < \mathrm{T}_{\max}$, go to Step 2, else finish the algorithm.

The chromosome g with the maximum fitness in set G_4 is the optimum solution.

4. Application

4.1. Background

This study used the Lucheng District, Ouhai District, and Longwan District of Wenzhou in Zhejiang Province as the region of application. Wenzhou is an emerging costal city with a developed economy and its total economy is the third largest in the province and the eighth of the cities in the Yangtze River delta. The GDP of Wenzhou in 2008 was 242.43 billion Yuan [21]. These three districts are downtown of Wenzhou, the quantity of private cars is 42.4/100 households [22]. Moreover, Wenzhou is a coastal port city, which is located to the south downstream of the Oujiang River and on the verge of the East China Sea.

Typhoons land in Wenzhou frequently, e.g. 9417 typhoon "Fred" and 9711 typhoon "Winnie" storm surge have brought great losses to Wenzhou. Figure 5 shows the risk map of inundation based on 100-year typhoon storm surges, which was drafted by the National Marine Environmental Predicting Center. The shadow part of the map is the area of storm surge inundation. Thus, the optimization of emergency traffic evacuation is necessary and significant for storm surge typhoons in urban areas of Wenzhou.

Twenty-three neighborhoods in these three districts were selected as evacuation sources (the research area is showed in the circle of Fig. 5). The evacuation network consists of the main roads, which are shown in Fig. 6. The number of vehicles that needed to be evacuated was 40% of the subscriber number in each neighborhood.

The evacuation targets for all of the vehicles from the 23 districts to the shelters were set. A shelter represented an area that was safe for vehicles and people, and the highways were the only routes to the safe area, so we selected the nodes in the Jin-li-wen Highway, Nantang Avenue, and Yong-tai-wen Highway as shelters. The vehicles were assumed to have arrived in a safe area after they passed the shelters.

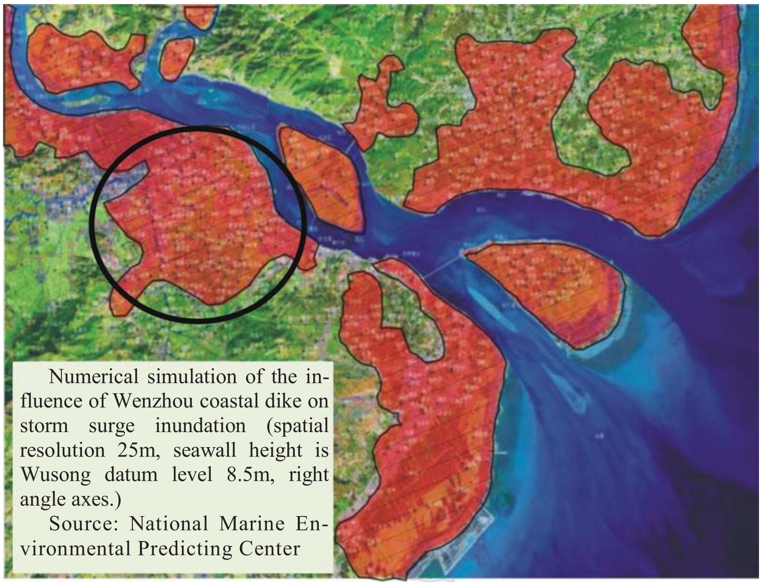

Fig. 5. Typhoon storm surge inundation once in a hundred years in Wenzhou.

Fig. 6. Evacuation network in the Wenzhou urban area.

The attributes of each arc included the name, serial numbers of the starting node and ending node, serial number of arc, distance, given travelling speed, and given flow. The values of the given travelling speed and flow were based on Design Specification for Highway Route (JTG D20-2006). Table 1 shows the attributes of some arcs.

4.2. Optimization results

The parameters of the network were the distance L_{ij}, given speed S_{ij}, given flow Q_{ij}, the number of vehicles E_o that needed to be evacuated from evacuation sources, etc. The values of these parameters were based on actual roads. The other parameters of the network were assigned as follows: the number of evacuation sources was $O = 23$, the number of shelters was $D = 3$, the number of routes between each evacuation source and shelter was $K = 6$, the total number of routes from evacuation source V_o was $M = 18$, and the total number of routes from all evacuation sources was 414.

In the algorithm, the crossover and mutation probability can guarantee the depth and breadth of search. when the probability is too high, the algorithm can't

Table 1
Parameters of arc

Name	Starting node	Ending node	Serial number	Distance (km)	Given speed (km/h)	Given flow (v/h)
Ouhai Avenue	2	4	4	1.16	60	6
Jinxiu Road	30	29	5	0.92	90	12
Transit Highway	65	75	6	0.85	120	10
Yong-tai-wen Highway	10	9	7	6.79	120	12
Airport Road	9	11	8	0.45	90	8
. . . ..						

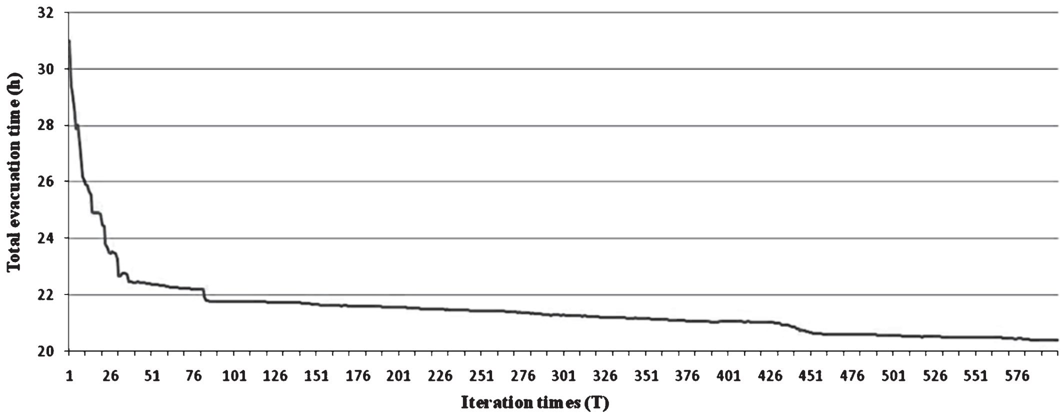

Fig. 7. Total evacuation time for each generation.

Table 2
Optimization results

Evacuation source	Shelter	The number of vehicles evacuated (veh)	Evacuation time (h)
Guoxi Town	Jin-li-wen Highway	3254	9.08
		195	14.17
		809	12.63
		0	0
		1285	14.24
		411	10.33
	Nantang Avenue	0	0
		411	12.77
		0	0
		458	12.84
		56	15.59
		0	0
	Yong-tai-wen Highway	0	0
		0	0
		0	0
		0	0
		0	0
		0	0

find the optimization solution; when it is too low, the algorithm can't convergence. So, the crossover I probability was $P_c^{(1)} = 0.9$, the crossover II probability was $P_c^{(2)} = 0.8$, the mutation probability was $P_m = 0.02$, the maximum iterations was $T_{max} = 600$, and the population size of the set of chromosomes G was $B = 100$.

The blue curve in Fig. 7 represents the total evacuation time max $\left\{T_{od}^{(k)}\right\}$ for each generation. This shows that the evacuation time reduced gradually after the first generation and it remained stable until after the 450th generation. The total evacuation time max $\left\{T_{od}^{(k)}\right\} =$ 20.43 hours when the generation reaches the maximum generation $T_{max} = 600$. This was the optimized result.

If all the vehicles were evacuated in a route where distance was the shortest, the total evacuation time was 40.50 hours. If the evacuation vehicles were distributed equally on every route, the total evacuation time was 34.92 hours. The results of these two evacuation processes were worse than the optimized result. Thus, the model proposed in this paper aided the decision-making process.

Table 2 shows the results for evacuation optimization in Guoxi Town in Ouhai District. There were six routes from the evacuation source Guoxi Town to each of the three shelters: Jin-li-wen Highway, Nantang Avenue, and Yong-tai-wen Highway. The number of evacuation vehicles and the evacuation time on these 18 routes are shown in Table 2. The route was not used for evacuating vehicles if the number of vehicles was 0 on this route.

The first row in Table 2, for example, represents the evacuation route from Guoxi Town to Jin-li-wen Highway, where the number of evacuation vehicles was 3254 and the evacuation time was 9.08 hours.

5. Conclusions and further research

This study established a multi-source and multi-destination network model to solve the VRA problem. The evacuation sources and common nodes were mixed in the model, which were consistent with the actual characteristics of densely populated cities. The travelling time was calculated based on the distance, the number of vehicles, the given speed, and the flow of the arc. This method was more accurate than the traditional minimum cost flow model for describing the vehicle flow characteristics. A modified GA was designed to solve the complex VRA problem. In a simulation of an emergency evacuation in Wenzhou, the algorithm delivered a 34% improvement compared with the initial solution.

There are several further research directions: Firstly, developing a method to obtain an accurate travel time based on the actual travelling conditions; Secondly, the model does not consider the effects on the evacuation process caused by other factors in the network, such as the original vehicles present in the network before the evacuation, vehicles that do not obey the traffic rules, broken roads, and traffic accidents, so the integration of these actual factors in the model requires further research; Finally, the model used in this study had a static distribution. Thus, it only focused on the distribution of vehicles on the original evacuation routes without considering the dynamic travel of vehicles throughout the network.

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