# Research on Public Vehicle Evacuation Path Planning Model Based on Spatiotemporal Network

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**Abstract.** This study aims to improve the efficiency of public vehicle evacuation during large-scale disasters by minimizing travel and waiting times for individuals and vehicles. To accomplish this, an S-curve behavior model was used to estimate evacuation demand, and a network model was developed to consider temporal and spatial factors of gathering points. A hybrid genetic algorithm and simulated annealing approach were utilized with an "enumerate then optimize" strategy and a step to temporarily retain optimal solutions for refinement. The effectiveness of the proposed model and algorithms was demonstrated in a case study of a typhoon evacuation in Chikan District, providing valuable insights for urban evacuation planning.

**Keywords:** Public vehicle;Vehicle evacuation path;Spatiotemporal demand node;Hybrid genetic simulated annealing algorithm; S-shaped behavior curve.

## 1. Introduction

The statement suggests that governments should conduct evacuations for residents during the extended warning period preceding a severe disaster. It highlights that a considerable portion of the population (25%-30%) relies on public transportation.

During public vehicle evacuations, the allocation of vehicles from shelters to assembly points and route planning is crucial. This process, known as the Bus Evacuation Problem (BEP) [1], is derived from the Vehicle Routing Problem (VRP). BEP models aim to minimize total evacuation time[2], cost[3], or maximize the number of people evacuated[4]. They also consider vehicle capacity constraints, referred to as the Capacitated Vehicle Routing Problem (CVRP) [5], and account for uncertainties in evacuation demand, roads, and shelters, requiring Dynamic VRP (DVRP) methods[6]. Heuristic algorithms are commonly used to solve BEP models due to their computational complexity, including genetic [7] and greedy algorithms [8]. Some studies have developed exact algorithms like column generation [9] and branch-and-cut algorithms[10]. However, existing research often overlooks crowd response time to evacuation orders and vehicle waiting scenarios during emergency conditions.

This paper introduces a model for public vehicle evacuation route planning, presents an improved algorithm to solve the problem, and demonstrates its practical value through a typhoon evacuation case in Chikan District.

## 2. Model

This section analyzes the generation of evacuation demands and describes the spatial and temporal evacuation demand network for assembly points, leading to the establishment of a public vehicle evacuation route model.

### 2.1 Problem description and hypothesis

Public vehicles are essential in the evacuation process, as they transport individuals to designated shelters within a set timeframe, based on demand generated at each assembly point.The evacuation network is set to have $n$ assembly points and $m$ refuges, and the evacuation time $T$ is divided into $\mu$ time periods according to $\lambda$ time, and $\lambda-1$ time replication nodes are set for each assembly point. Therefore, this model contains $n\lambda$ demand nodes.

The basic assumptions of the model are as follows:

(1) Assembly points are divided into several nodes with evacuation demands in space and time.

(2) The total number of public vehicles is fixed, with the same capacity and maximum time.

(3) Public vehicles start and end at shelters, allowing departure and return to shelters to be different.

(4) The demand for a moment node is only served by one vehicle.

### 2.2 Assembly point evacuation requirement

This paper explores how people's varying response times to an evacuation order lead to different evacuation demands over time. It utilizes an S-shaped behavior curve to estimate the percentage of evacuation demands for each time period, enabling the calculation of demands at different times for each assembly point, as outlined in a specific equation (1).

$$P(t)=\frac{1}{1+e^{-c(t-h)}} \tag{1}$$

Where $p(t)$ represents the cumulative percentage of the number of people generated by the assembly point at the moment; $c$ indicates the speed at which personnel respond to an evacuation command. $h$ is the time for half of the demand in the evacuation process; $t$ indicates a timing.

### 2.3 Model building

2.3.1 symbol description

Table 1 shows the parameter symbols, decision variables for the construction of the model.

Table 1. Parameters and variables

| symbol | | meaning | symbol | | meaning |
|---|---|---|---|---|---|
| index | $i,j$ | Assembly point or Shelter sign | parameter | $t_{ij}$ | Travel time between any two nodes, $t_{ij}=d_{ij}/v$ （ $i,j\in V$ , $v$ is the vehicle speed） |
| | $k$ | Vehicle identification | | $Q_k$ | The maximum number of people loaded in vehicle $k(k\in K)$ |
| set | $V$ | Node set, $V=R\cup P'$ | | $L_k$ | The maximum time for vehicle $k$ to complete an evacuation |
| | $R$ | Set of shelters | | | |
| | $P$ | Set of assemblies | decision variables | $x_{ijk}$ | The binary variable which is 1 if and only if the vehicle $k(k\in K)$ travels from node $i$ concerned to node $j$ ( $i,j\in V$ ) |
| | $P'$ | Set of assemblies (include replication nodes) | | $y_{ik}$ | The binary variable which is 1 if and only if the vehicle $k(k\in K)$ departs from the node $i(i\in p')$ |
| | $r_i$ | Demand at meeting $i(i\in P')$ | | $y_{ki}$ | The binary variable which is 1 if and only if the vehicle $k(k\in K)$ arrives node $i(i\in p')$ |

| | | | | | |
|---|---|---|---|---|---|
| | $d_{ij}$ | The distance between any two nodes $(i, j \in V)$ | | $a_{ki}$ | The time when vehicle $k(k \in K)$ arrives at assembliy $i(i \in V)$ |

2.3.2 Mathematical model

The model constructed in this paper is as follows:

$$\min \sum_{i\in V}\sum_{j\in V}\sum_{k\in K} t_{ij}x_{ijk} + \sum_{i\in P'}\sum_{k\in K} | t_i - a_{ki} | y_{ki} \tag{2}$$

$s.t.$

$$\sum_{k\in K} y_{ik}, \forall i \in P' \tag{3}$$

$$\sum_{i\in V}\sum_{k\in K} x_{ijk} = 1, \forall j \in P' \tag{4}$$

$$\sum_{j\in V}\sum_{k\in K} x_{ijk} = 1, \forall i \in P' \tag{5}$$

$$\sum_{i\in V} x_{ijk} = \sum_{m\in V} x_{jmk}, \quad \forall j \in V, k \in K \tag{6}$$

$$\sum_{i\in R}\sum_{k\in K} x_{ijk} = | K |, \forall j \in P' \tag{7}$$

$$\sum_{i\in P'}\sum_{j\in R} x_{ijk} = 1, \forall k \in K \tag{8}$$

$$\sum_{k\in K} x_{ijk} + y_{ik} + y_{kj} \le 2, \quad \forall i, j \in R \tag{9}$$

$$\sum_{i\in V} x_{ijk} \ge y_{jk}, \quad \forall j \in V, k \in K \tag{10}$$

$$a_{jk} \ge \max(a_{ik}, t_i) + t_{ij} - M(1 - x_{ijk}), \forall i \in p', j \in V \tag{11}$$

$$a_{jk} \le \max(a_{ik}, t_i) + t_{ij} + M(1 - x_{ijk}), \forall i \in p', j \in V \tag{12}$$

$$\sum_{i\in V} r_i y_{ik} \le Q_k, \forall k \in K \tag{13}$$

$$\sum_{i\in V}\sum_{i\in V} t_{ij}x_{ijk} + \sum_{i\in P'} \max[(t_i - a_{ik})y_{ik}, 0] \le L_k, \forall k \in K \tag{14}$$

$$y_{ik} \ge y_{i+|P|,k} \Rightarrow \sum_{m\in V, m\neq i+2|P|} x_{i+|P|,mk} = 1, \forall i \in P', k \in K \tag{15}$$

$$x_{ijk}, y_{ik}, y_{ki} \in \{0,1\}, \forall i, j \in V, k \in K, a_{ik} \ge 0, \forall i \in P', k \in K \tag{16}$$

The objective function in this paper has two parts: travel time and combined waiting time. Equations (3)-(16) establish different constraints for the model. These include visiting all demand points, allowing only one vehicle at each point, requiring the same vehicle to visit and depart from each point, and having vehicles depart and return to shelters. Other constraints include establishing connections between nodes, setting capacity and time limits for vehicles, and defining decision variables.

# 3. Hybrid genetic simulated annealing algorithm

The paper discusses the challenges of considering multiple shelters, assembly points, vehicle status, and diverse origins and destinations in vehicle routing. To solve this problem, the paper proposes a hybrid genetic simulated annealing algorithm.

### 3.1 Pretreatment

3.1.1 Chromosome coding

Chromosome coding takes the form of real number coding. A solution can be expressed in the form $chrom = \{(Ri, P1, \ldots Ph), \ldots (Rz, P1, \ldots Pl)\}$ , $(Ri, P1, \ldots Ph)$ represents a vehicle path. In the evacuation process, vehicles start from nearby refuges, collect demands from multiple points, and return to the nearest refuge corresponding to each demand node. To handle the challenge of identifying replication nodes as the demand increases, a two-digit numbering system is used, where the first digit represents the moment and the second digit represents the assembly point.

3.1.2 The initial feasible solution is generated

Define node set $V$ , shelter set $R, r \in R$ ,assembly point set $P$ , time constant $T$ ,vehicle travel $Route(t,c), t \in 1,2,\ldots T, c \in P$ ,set at evacuation time $U(t), t \in 1,2,\ldots T$ ,Node travel time $table(s,s), s \in V$ ,Vehicle running time $th$ ,mutation probability $pc$ ,evacuation interval $\mu$ , When the vehicle selects the demand point, it faces two choices. One is deciding whether to wait after loading the demand, as detailed in algorithm 1. The other is determining when to load the demand, as outlined in algorithm 2. See Table 4 for algorithm 1 and 2.

### 3.2 Algorithm solution flow

The process of hybrid genetic simulated annealing algorithm is shown in Figure 1.

## 4. Case analysis

This section explains a simulation experiment that uses a model to plan public vehicle paths for evacuating people before a typhoon. The experiment focuses on evacuating Chikan District in Zhanjiang City, Guangdong Province, when a typhoon is expected to hit Potou District. The evacuation area covers a 10km radius from the point of impact and has 9 gathering points and 2 shelters. Distances are calculated using Google Maps. The evacuation area is divided into 14 zones, and people are allocated based on their distance to each gathering point. If demand exceeds a vehicle's capacity, the nearest shelter sends the vehicle back at full capacity. The model also considers vehicle paths when there are only a few people left at a gathering point. The simulation results are shown in Table 3.

Assuming there are 35 vehicles with an 80-person capacity, the 9 gathering points are expanded to 108 demand nodes. The hybrid genetic simulated annealing algorithm is run six times, and the best results are presented in Table 2.

## 5. Conclusion

The paper focuses on using public vehicles for large-scale disaster evacuations. It examines evacuation characteristics, develops mathematical models and algorithms to design evacuation routes for public vehicles, and creates a feasible evacuation plan for Typhoon evacuation in Chikan District, Zhanjiang City. The study finds that the response time of the crowd affects demand at different gathering points, indicating that considering waiting time can improve vehicle utilization and occupancy rates. Future research could explore uncertainties in people reaching gathering points, multiple possible vehicle travel paths, and the reuse of evacuation vehicles.

Table 2. Calculation result

| | value |
|---|---|
| Total evacuation time (min) | 638 |
| Average vehicle travel time (min) | 56 |
| Average vehicle travel time (min) | 32 |

| | |
|---|---|
| load factor $LF$(%) | 90.5% |

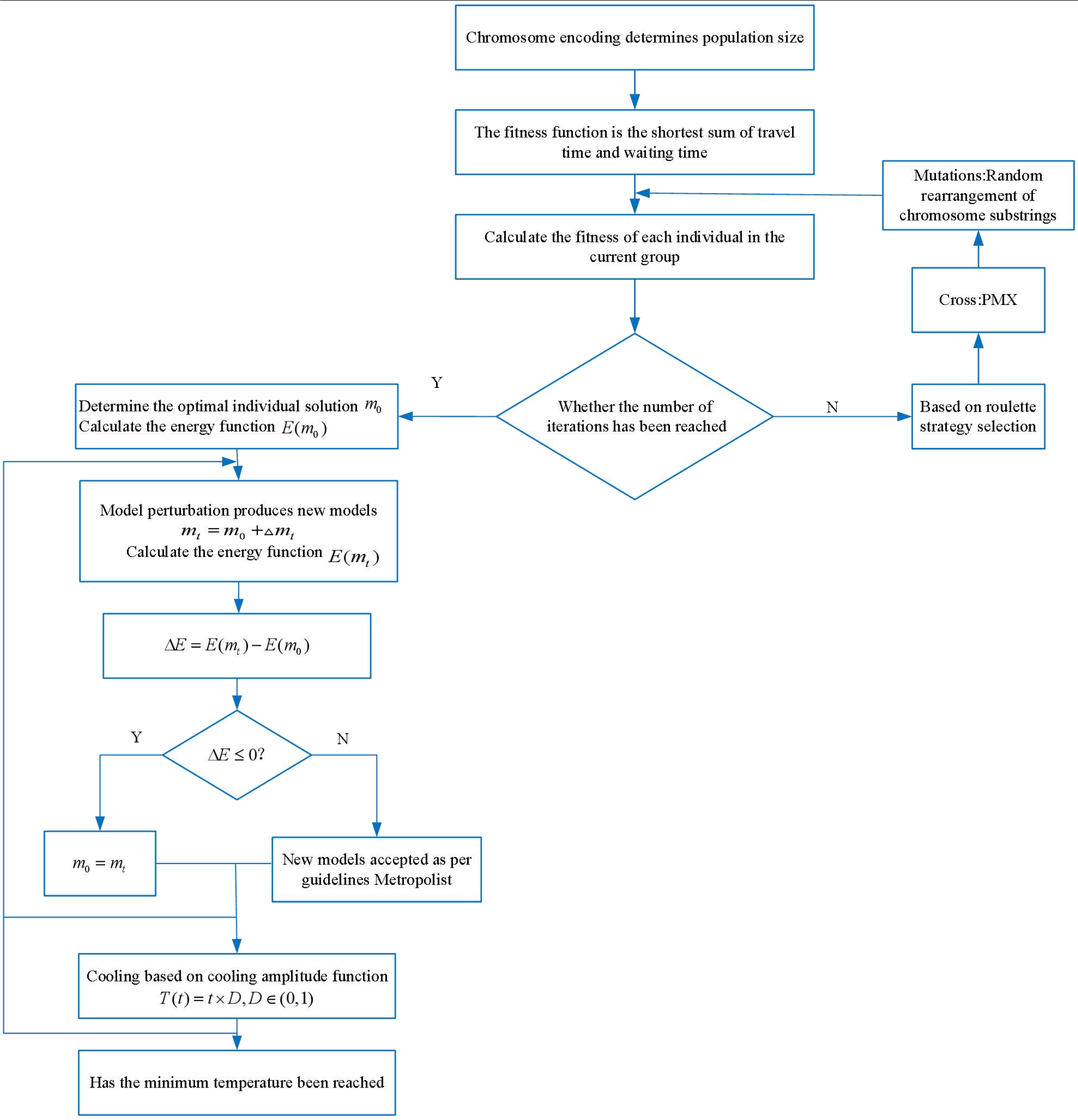


Fig. 1. Hybrid genetic simulated annealing algorithm

Table 3. Number of evacuees at assembly point

| time / rally point | Waiting number | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| 1 | 1 | 3 | 16 | 1 | 49 | 62 | 62 | 49 | 1 | 16 | 3 | 1 |
| 2 | 1 | 4 | 21 | 28 | 15 | 10 | 10 | 14 | 28 | 21 | 4 | 1 |
| 3 | 3 | 14 | 77 | 5 | 75 | 57 | 57 | 75 | 5 | 77 | 14 | 3 |
| 4 | 0 | 1 | 5 | 24 | 35 | 77 | 77 | 34 | 24 | 5 | 1 | 0 |
| 5 | 0 | 1 | 3 | 16 | 70 | 31 | 31 | 69 | 16 | 3 | 1 | 0 |
| 6 | 1 | 6 | 29 | 72 | 52 | 1 | 1 | 52 | 72 | 29 | 6 | 1 |
| 7 | 0 | 2 | 9 | 49 | 56 | 42 | 41 | 56 | 49 | 9 | 2 | 0 |
| 8 | 1 | 5 | 27 | 61 | 74 | 3 | 3 | 74 | 60 | 27 | 5 | 1 |
| 9 | 1 | 4 | 21 | 30 | 13 | 6 | 6 | 13 | 29 | 21 | 4 | 1 |

Table 4. Number of evacuees at assembly point

Algorithm1.Decide whether to wait at this point or go to the next rally point

If $U(i-1) \le th < U(i)$

$p = 1 - ((U(\mathrm{i}) \text{-} th)/\mu) \times pc$

Algorithm1.Decide whether to wait at this point or go to the next rally point

Else
$p = 0$
The roulette strategy generates judgment parameters $I(p)$, Wait when $I = 1$, $I = 2$ to proceed to next rally point

Algorithm 2.Decide which moment of demand to carry

Current vehicle at rally point $c'$, Last rally point $c$
If $U(i-1) \le th < U(i)$
$p = 1 - ((th\text{-}U(\text{i-1}))/\mu) \times pc$
Else
$p = 1$
$pickfirst = \text{abs}(th\text{-min}([table(c,c') \;\; table(r,c')]))/\text{min}([table(c,c') \;\; table(r,c')]))$, $h$ =rank
The roulette strategy generates judgment parameters $I(p)$
If $I = 1$
If $U(i-1) \le th < U(i)$
If $pickfirst$<=0.2 and $h$<=1-$pickfirs$
$Route(next\ tc) = (i-2)c', Route(next+1\ tc) = (i-1)c'$
Else
$Route(next\ tc) = (i-1)c'$
If $th \ge U(T)$
If $pickfirst$<=0.2 and $h$<=1-$pickfirs$
$Route(next\ tc) = (T-1)c', Route(next+1\ tc) = Tc'$
Else
$Route(next\ tc) = Tc'$
Else
Requirements at the moment after carrying the rally point $c'$

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