A Study on Maximizing Traffic Reachability in Contingency Scenarios Based on Genetic Algorithms

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Abstract. This paper presents a study on maximizing traffic demand accessibility in transportation networks under contingency scenarios using genetic algorithms. Transportation demand accessibility is defined as the proportion of allocated traffic that can reach its destination, considering potential disruptions in the network. The study begins by formulating a model for calculating transportation demand accessibility between different origin-destination pairs, taking into account the possibility of unforeseen events on any road segment. By applying genetic algorithms, the study aims to optimize the allocation of traffic flows in a way that maximizes the expected reachability across the network, even when multiple road sections experience contingencies. Several scenarios are considered, including the introduction of capacity constraints on road segments and varying traffic demands. The results demonstrate that the proposed method can effectively optimize traffic flow allocation, enhancing the robustness and efficiency of transportation networks under uncertain conditions. This research provides valuable insights for urban planners and traffic managers seeking to improve network resilience in the face of unexpected disruptions.

Keywords: Transportation Network, Traffic Flow Allocation, Expected Accessibility, Roadway Contingencies.

1. Introduction

As the economy develops and society progresses, urbanization continues to advance, leading to increasing demands for safe, efficient, and diversified travel modes [1, 2]. Future cities are expected to adopt self-driving technology as a primary mode of transportation, integrating it into urban planning to establish transportation networks that are more sustainable and responsive to the needs of their residents [3, 4]. However, different allocations of transportation demand significantly affect the efficiency of urban transportation operations, and varying levels of accessibility can have diverse impacts on citizens' travel behaviors [5, 6].

In light of these changes, understanding and optimizing transportation demand accessibility is crucial for building resilient and efficient urban transportation systems [7]. Traditional approaches to modeling transportation networks often fall short in accounting for the dynamic and uncertain nature of urban environments [8, 9]. This study addresses these limitations by employing a genetic algorithm to optimize traffic flow allocation, aiming to maximize expected accessibility across the network, even in the face of contingencies such as infrastructure failures or natural disasters. By considering the integration of self-driving technology and the probability of unforeseen events, this research provides valuable insights for urban planners and policymakers to enhance the resilience and efficiency of transportation networks in future cities.

2. Modeling Traffic Accessibility in Simplified Networks

The data in this paper originates from 51mcm.cumt.edu.cn. This study begins the formula for calculating the transportation demand accessibility. Given an origin and destination pair (s,t), the transportation demand accessibility is from the origin s to the destination t the proportion of allocated traffic that can actually reach the destination. The formula is:

$$AR_{(s,t)} = \frac{\sum_{r \in R_{(s,t)}} F_{r,(s,t)} \cdot a_{r,(s,t)}}{T_{(s,t)}} \quad (1)$$

Where $R(s,t)$ is from the starting point s to the end point t the set of all possible paths, andF_r is the traffic volume assigned to the path$r$ is the traffic volume assigned to the path, and$T(s,t)$ is the amount of traffic assigned to the path s to the end point t is the total traffic demand for the(s,t) the total traffic demand.

Since each road segment has the same probability of experiencing a contingency, and assuming that these events are independent, the expected accessibility of the traffic demand can be obtained by calculating the average of the accessibility rates for all possible contingencies.

In a transportation network, it is assumed that the probability of an unforeseen situation on each road section is$P$, and that these events are independent. For a given (origin, destination) pair(s,t) , its traffic demand accessibility$AR_{(s,t)}$ depends on the state of each road segment in the network and the amount of traffic assigned to each path.

First, define$R(s,t)$ to be the set of all possible paths of (start, end) to the (s,t) the set of all possible paths. For each path$r \in R(s,t)$, define F_r to be the traffic volume assigned to the path r the amount of traffic assigned to the path, and$T(s,t)$ is the (start, end) demand for the(s,t) the total traffic demand.

In the absence of any roadway failure, the traffic demand reachability rate $AR_{(s,t)}$ is 1 because all assigned traffic reaches the destination. However, when a roadway segment fails, only those traffic volumes on the path that do not pass through the segment reach their destinations.

In order to calculate the desired accessibility of the traffic demand$EAR_{(s,t)}$, it is necessary to consider all the possible combinations of states of the roadway and to compute the expected accessibility of each state (origin, destination) to the (s,t) the reachability of each state. Since the probability of a contingency situation on each road segment is$P$ and the probability of no unexpected situation is$1-P$, we can use the expectation formula in probability theory to compute$EAR_{(s,t)}$.

For the (origin, destination) pair (s,t) , the expected accessibility of its corresponding traffic demand$EAR_{(s,t)}$ can be expressed by the following equation:

$$EAR_{(s,t)} = \sum_{r \epsilon R_{(s,t)}} (1-P)\frac{F_{r',(s,t)} a_{r',(s,t)}}{T_{(s,t)}} + P\frac{F_{r^*,(s,t)} \cdot a_{r^*,(s,t)}}{T_{(s,t)}} \quad (2)$$

With this formula, we can calculate that each path$r$ reachability without any roadway failure is 1, which corresponds to the actual situation. On this basis, multiply the amount of traffic assigned to that pathF_r with the total traffic demand$T(s,t)$ ratio, and then adding up the accessibility rates of all paths, we can calculate the accessibility rate from the starting points to the end point$t$ the desired accessibility of the traffic demand from the origin to the destination.

To simplify the model-solving process, this section first constructs a simple transportation network model, as shown in Figure 1.

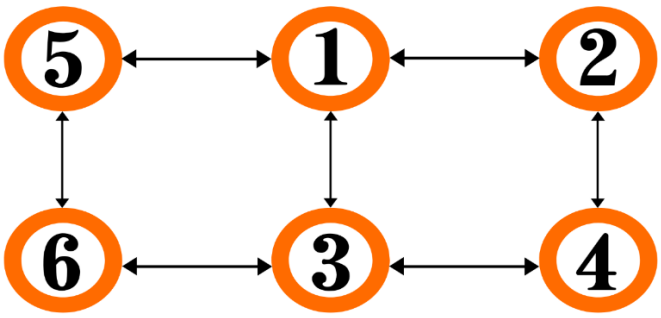


Figure 1. Schematic diagram of a simple transportation network.

Now we want to give the traffic volume assigned to the corresponding paths by the traffic demand between each (origin, destination) pair, so that when a contingency occurs on any 1 road section in the network (each road section has the same probability of having a contingency), the expected reachability of all the traffic demand in the network is maximized. For this simple transportation network, we assume that we need to consider two (start, end) pairs, (1, 6) and (1, 4), respectively. In

order to increase the robustness of the model, we assume that their traffic demands are unequal, 300 and 100, respectively. Obviously, we can make the following table 1 for this traffic network:

Table 1. Schematic diagram of different (start, end) pairs of demand and possible paths.

(Starting point, end poing)	quantity demanded	Possible pathways
(1,6)	300	1-3-6 1-5-6
(1,4)	100	1-2-4 1-3-4

The next calculation is carried out. From the traffic network diagram, we can see that there are 14 road sections in the diagram, so we assume that the probability of emergencies on each road section is$\frac{1}{14}$. Let 3-6 allocate traffic volume asx_1 3-4 allocate traffic volume isx_2 , and the assigned traffic volume of each road section is shown in the figure 2.

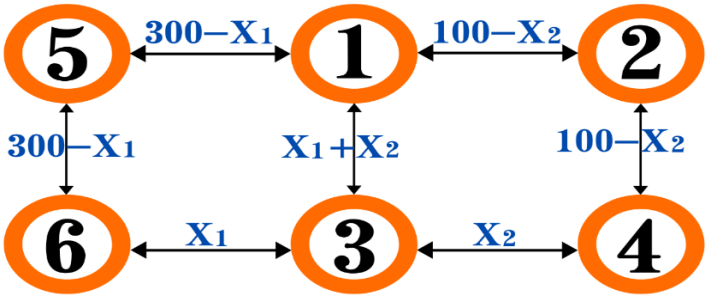


Figure 2. Schematic diagram of assigned traffic volumes for the following road sections.

Then, for each roadway segment, the traffic volume in the event of a contingency can be expressed by the following equation:

$$X_{15} = 400 - (300 - x_1) \quad (3)$$

$$X_{56} = 400 - (300 - x_1) \quad (4)$$

$$X_{12} = 400 - (100 - x_2) \quad (5)$$

$$X_{24} = 400 - (100 - x_2) \quad (6)$$

$$X_{13} = 400 - (x_1 + x_2) \quad (7)$$

$$X_{36} = 400 - x_1 \quad (8)$$

$$X_{34} = 400 - x_2 \quad (9)$$

$$X_{51} = X_{65} = X_{21} = X_{42} = X_{31} = X_{63} = X_{43} = 400 \quad (10)$$

Where.X_{ij} Denotes the traffic volume of the whole network when there is an unexpected situation in i-j road sections. From the above equation, the desired accessibility of this transportation networkEAR is:

$$A = \frac{1}{14} \times (X_{15} + X_{56} + X_{12} + X_{24} + X_{13} + X_{36} + X_{34}) \quad (11)$$

$$B = \frac{1}{14} \times (X_{51} + X_{65} + X_{21} + X_{42} + X_{31} + X_{63} + X_{43}) \quad (12)$$

$$EAR = (A + B) \times \frac{1}{400} = 85.71\% \quad (13)$$

It follows that in the case of a symmetric transportation network, even if the traffic demand is asymmetric, no matter how the traffic is distributed, the expected reachability rateEAR is a constant, which is similar to the condition of Problem 1. Therefore, for Problem 1, the expected accessibility is also a constant.

As a transportation planning problem, this study first defining the decision variables, we assume$F_{r,(s,t)}$ to be the variable from the starting point s to the end point t through the path r of traffic passing through the path. In this problem, the objective we wish to achieve is to maximize the desired reachability of the traffic demand for all paths.EAR Is maximized. Then we construct the following objective function:

$$\max f_1 = \sum_{(s,t)} \left(\sum_{r \epsilon R_{(s,t)}} (1-P) \frac{F_{r',(s,t)} a_{r',(s,t)}}{T_{(s,t)}} + P \frac{F_{r^*,(s,t)} \cdot a_{r^*,(s,t)}}{T_{(s,t)}} \right) \tag{14}$$

Next we look for the constraints in achieving the goal, the main ones being the following.

The first is the conservation of traffic, i.e., from s departures and arrivals t of the total traffic must be equal to its total traffic demand, as shown in the following equation:

$$\sum_{r \epsilon R_{(s,t)}} F_{r,(s,t)} = T_{(s,t)} \tag{15}$$

In addition to this, we note that the number of paths used between each (start, end) pair is no more than 5, and call this a path selection constraint, assuming that$a_{r,(s,t)}$ is a constraint on the number of pairs of(s,t) Whether or not to use paths$r$ which:

$$a_{r,(s,t)} = \begin{cases} 0, (s,t) \text{ without r} \\ 1, (s,t) \text{ with r} \end{cases} \tag{16}$$

Well, based on the above analysis there is:

$$\sum_{r \epsilon R_{(s,t)}} a_{r,(s,t)} \leq 5 \tag{17}$$

Since the traffic assigned to path r cannot exceed the total traffic demand from that origin to the destination, we have the following equation:

$$F_{r,(s,t)} \leq T_{(s,t)} \cdot a_{r,(s,t)} \tag{18}$$

Also, all traffic is non-negative, ie:

$$F_{r,(s,t)} \geq 0 \tag{19}$$

For the solution of this model, we can use genetic algorithm. Genetic algorithm is a stochastic parallel search algorithm, its basic idea is: first coding the individuals to generate the initial population, and then start to evolve, using the fitness function to judge the individual's superiority and inferiority, the excellent individual will have a higher probability of obtaining the opportunity to replicate, crossover and mutation, and so on, until meet the termination conditions of the iteration, so as to get the optimal solution[10].

Based on the above model and the solution process, this study obtain the corresponding optimal planning paths and their assigned traffic volumes for the (start,end) pairs of (1,9) and (3,7), respectively, as shown in the following table 2.

Table 2. Simplified Calculation Results.

(Beginning, end)	Planning path	Distribution of traffic
(1,9)	1-4-5-6-9	119
	1-2-5-8-9	53
	1-2-5-6-9	2
	1-4-5-8-9	2
	1-2-3-6-9	1
(3,7)	3-6-5-4-7	59
	3-6-5-8-7	14
	3-2-5-4-7	3
	3-2-5-8-7	2
	3-6-9-8-7	2

3. Optimization of Traffic Network under Roadway Contingencies

To further expand the scope of the study, new conditions are introduced. This research sets up a more complex transportation network, allowing for contingencies on any 5 road segments. Such a scenario complicates the calculation and maximization of accessibility rates, so this study optimizes the simplified model to address the impact of multiple road blockages.

Building upon the research from the previous section. Still define $F_{r,(s,t)}$ as the distance from the starting point s to the end point t through the path r which is also our decision variable. At this point, our objective function is to maximize the expected reachability of all (origin, destination) pairs under all possible combinations of 5 roadway contingencies EAR .

Since it would be very complicated to consider all possible combinations of 5 roadway contingencies directly, we can use random sampling or approximation methods to estimate the expected reachability. A common approximation method is the scenario-based approach, where multiple sets of 5 roadway failure scenarios are randomly generated and the reachability rate is calculated for each set of scenarios and then averaged as an estimate of the expected reachability rate.

Suppose that the generation of N group of scenarios, in which the first i group of scenarios has 5 road segments failing, and this group of scenarios (start point,end point) has the same effect on the (s,t) The expected reachability EAR in this group of scenarios (start point, end point) can be expressed as follows:

$$EAR \approx \frac{1}{N}\sum_{i=1}^{N}\left(\sum_{(s,t)}\left(\sum_{r\epsilon R_{(s,t)}}(1-P)\frac{F_{r',(s,t)}a_{r',(s,t)}}{T_{(s,t)}}+P\frac{F_{r^*,(s,t)}\cdot a_{r^*,(s,t)}}{T_{(s,t)}}\right)\right) \tag{20}$$

$$\max\ f_2 = \frac{1}{N}\sum_{i=1}^{N}\left(\sum_{(s,t)}\left(\sum_{r\epsilon R_{(s,t)}}(1-P)\frac{F_{r',(s,t)}a_{r',(s,t)}}{T_{(s,t)}}+P\frac{F_{r^*,(s,t)}\cdot a_{r^*,(s,t)}}{T_{(s,t)}}\right)\right) \tag{21}$$

The constraints in this scenario are essentially the same as in the first, starting with the still assumed $a_{r,(s,t)}$ as the constraints on (s,t) whether the path is used r which:

$$a_{r,(s,t)} = \begin{cases} 0, (s,t) \text{ without } r \\ 1, (s,t) \text{ with } r \end{cases} \tag{22}$$

The constraints are organized into the following system of equation

$$\begin{cases} \sum_{r\epsilon R_{(s,t)}} F_{r,(s,t)} = T_{(s,t)} \\ \sum_{r\epsilon R_{(s,t)}} a_{r,(s,t)} \le 5 \\ F_{r,(s,t)} \le T_{(s,t)} \cdot a_{r,(s,t)} \\ F_{r,(s,t)} \ge 0 \end{cases} \tag{23}$$

For the solution of this model, the study continues to use the genetic algorithm. However, compared to the simplified scenario, we need to adjust and optimize the model to account for the increased complexity, ensuring that the algorithm can effectively search the solution space and identify the best solution. Due to the larger size of the transportation network and the increased number of (start, end) pairs in Problem II, the search space expands, and the chromosome length increases. Furthermore, in Problem II, the fitness function needs to evaluate the expected reachability of any 5 road segments when a contingency occurs, which adds to the complexity of the model and enlarges the solution space. To handle the more complex nature of Problem II, the initial population of the genetic algorithm may need to be more diverse to ensure a broader solution space is covered.

Based on the above model and the solution process, we obtain the corresponding optimal planning paths and their assigned traffic volumes for the (start, end) pairs of (27, 6) and (19, 25), respectively, as shown in the following table 3.

Table 3. Calculation Results under Complex Conditions.

(Beginning, end)	Planning path	Distribution of traffic
(27,6)	27-35-41-8-9-5-6	41
	27-35-41-10-9-5-6	26
	27-35-28-8-9-5-6	18
	27-35-41-10-16-5-6	6
(19,25)	19-10-11-12-7-33-25	88
	19-20-11-12-7-33-25	63
	19-10-41-35-27-33-25	15
	19-10-41-35-27-30-25	8

4. Maximizing Reachability with Road Capacity Limitations

Furthermore, to better reflect real-world conditions, this study introduces capacity constraints for the paths. On the basis of the existing model, road segment capacity limitations are added to ensure that the expected accessibility rate of all traffic demand in the network is maximized, even when contingencies occur on any 5 road segments. We continue to use the genetic algorithm, but a penalty function is added to the final objective function when calculating individual fitness. This approach decreases the probability of selecting traffic allocation schemes that exceed path capacity limits, allowing the optimal solution to be obtained through iterations.

Still defining from the beginnings to the end pointt through a pathr the amount of traffic that passes through the path$F_{r,(s,t)}$ as the decision variable for this question.

The desired reachability needs to be maximized while considering the capacity constraints of the road sectionEAR , the expression of the objective function for this question is as follows:

$$\max f_3 = \frac{1}{N}\sum_{i=1}^{N}\left(\sum_{(s,t)}\left(\sum_{r\epsilon R_{(s,t)}}(1-P)\frac{F_{r',(s,t)}a_{r',(s,t)}}{T_{(s,t)}} + P\frac{F_{r^*,(s,t)}\cdot a_{r^*,(s,t)}}{T_{(s,t)}}\right)\right) \tag{24}$$

Their corresponding constraints are shown below.

First, the traffic volume is conserved. The amount of traffic traveling from$s$ starting point and arriving att the total traffic volume must be equal to the starting point, the end point to the(s,t) the traffic demand between is:

$$\sum_{r\epsilon R_{(s,t)}} F_{r,(s,t)} = T_{(s,t)} \tag{25}$$

Second, the non-negative constraint is satisfied, i.e., all traffic volumes are non-negative:

$$F_{r,(s,t)} \geq 0 \tag{26}$$

Thirdly, there is a need to meet the capacity constraints of road sections to ensure that the traffic volume on each road section does not exceed its capacity limit:

$$\sum_{e\epsilon r,(s,t)} F_{r,(s,t)}\cdot a_{r,(s,t)} \leq C_e \tag{27}$$

WhereC_e denotes the section of road$e$ of the capacity ceiling.

The fourth is the path selection constraint, i.e., the number of paths used between each (start, end) pair is not more than 5. Assumptions

$$a_{r,(s,t)} = \begin{cases} 0, (s,t) \text{ without r} \\ 1, (s,t) \text{ withr} \end{cases} \tag{28}$$

Based on the above constraints, we have:

$$\sum_{r \epsilon R_{(s,t)}} a_{r,(s,t)} \leq 5 \tag{29}$$

Where.a Is (start, end) for (s, t) whether to use the path or not$r$ the decision function of (s, t).

Finally, path planning traffic volume constraints need to be satisfied:

$$F_{r,(s,t)} \leq T_{(s,t)} \cdot a_{r,(s,t)} \tag{30}$$

For the solution approach, we continue to apply the genetic algorithm, as in the previous section. However, adjustments are necessary to accommodate the new constraints to ensure the algorithm can effectively search the solution space and identify the optimal solution. Since this part of the study introduces traffic volume limits for road segments, a penalty is added to the allocation schemes that exceed these limits. The more the allocation exceeds the limit, the lower the probability of that scheme being selected. Additionally, this part requires calculating the total traffic volume for each road segment, which is achieved by using a loop to accumulate the traffic volume of all paths passing through each segment.

Based on the above model and the solution process, we obtain the corresponding optimal planning paths and their assigned traffic volumes for the (start, end) pairs of (32, 9) and (17, 8), respectively, as shown in the following table 4.

Table 4. Calculation Results under Capacity Constraints.

(Beginning, end)	Planning path	Distribution of traffic
(32,39)	32-24-7-12-11-10-19-18-2-15-13-39	40
	32-24-7-12-11-20-19-18-2-15-13-39	33
	32-24-7-12-11-10-16-36-3-42-38-39	32
	32-24-7-12-11-10-16-18-2-15-13-39	28
(17,8)	17-39-13-15-2-18-16-10-41-8	67
	17-39-38-42-3-36-6-7-9-8	42
	17-14-13-15-2-18-16-10-41-8	17

5. Conclusion

This study developed a model to optimize traffic accessibility in transportation networks while considering contingencies and capacity limitations. The model employs a genetic algorithm to maximize expected accessibility rates by distributing traffic across various paths between different origin-destination pairs. Through multiple scenarios, including cases with single and multiple roadway contingencies, the results indicate that, even under asymmetric traffic demands, the expected accessibility remains constant in symmetric networks. The model also incorporates capacity constraints to more accurately reflect real-world conditions, ensuring that traffic allocation does not exceed road capacities while achieving optimal accessibility. The findings provide a robust framework for optimizing transportation planning under conditions of uncertainty, emphasizing the importance of adaptability and flexibility in traffic management. By utilizing genetic algorithms and introducing random sampling and scenario-based approaches, this model effectively addresses the complexities involved in maintaining traffic flow under multiple contingency scenarios, offering valuable insights for urban planners and policymakers aiming to enhance network resilience and accessibility.

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