Advances in Industrial Engineering, Winter 2021, 55(1): 69-89
DOI: 10.22059/jieng.2021.326142.1784
RESEARCH PAPER

Reliable Urban Transportation Network Design Problem Considering Recurrent Traffic Congestions

Ali Riahi Samani[a], Seyyed-Nader Shetab-Boushehri[b], Reza Mahmoudi[c,*]

a. *Department of Civil Engineering, University of Memphis, Memphis, Tennessee, USA.*
b. *Department of Industrial and Systems Engineering, Isfahan University of Technology, Isfahan, Iran.*
c. *Department of Civil Engineering, University of Calgary, Calgary, Alberta, Canada.*

Received: 25 June 2021, Revised: 08 July 2021, Accepted: 10 July 2021

Abstract

Traffic congestion is one of the main reasons for the unsustainability of an urban transportation network. Changes in travel demand and streets' capacity lead to traffic congestion in urban transportation networks, which is known as recurrent traffic congestion. This study aims to assess the performance reliability of urban transportation networks subject to recurrent traffic congestion conditions in order to help travelers to find alternative non-congested routes. A non-congested route is a route without any congested link. The network reliability is defined and modeled as two different scenarios; users' unawareness of the network's traffic congestion and users' ongoing awareness of the network's traffic congestion. In addition, a reliable network design model is provided to optimize the reliability of the network taking into account street widening policy and budget constraints. Lastly, a Quantum-Inspired Evolutionary Meta-Heuristic Algorithm is adopted; while maintaining accuracy, to reduce problem-solving time and providing the possibility of solving large-scale problems for real networks. To show the applicability of the proposed models and algorithm, they have been implemented on the Sioux Falls transportation network. The results indicate users' awareness of traffic congestion in the network increases its reliability, and centrally located links are the first candidates for street widening.

Keywords:
Reliability;
Recurrent Traffic Congestion;
Traffic Awareness;
Sustainable Urban Transportation Network;
Network Design

Introduction

Urban communities depend on their transportation systems for their daily activities; inefficient performance of these systems can make the city unsustainable in all dimensions [1] which leads to a high level of dissatisfaction among its citizens [2, 3]. The quality of the provided services is the most important factor for Urban Transportation Network (UTN) users. Most complaints by users are about unpredictable congestions and travel time in the network [4]; one of the reasons being recurrent congestions. Recurrent congestions can be a result of two phenomena in the network: (1) changes in network's demand in a specific hour of the day; (2) and changes in the street capacity because of different reasons, such as accidents, bad driving, street maintenance, etc. [5].

Analyzing the performance of UTNs under Recurrent Traffic Congestions (RTCs) to find a practical solution for improving the level of service and sustainability of UTNs is necessary. However, evaluating the performance of UTNs concerning RTCs using traditional methods cannot provide reliable results. Traditional analysis of street networks is often based on average

* Corresponding author: (R. Mahmoudi)
Email: reza.mahmoudi@ucalgary.ca

values; for example, the average travel time obtained from static traffic assignment techniques. It is assumed that origin-destination demand and street capacity are constant over time, while the travel demand varies over time and the capacity of the streets may change for various reasons. Applying the average traffic flow alone is not sufficient to assess the networks' performance in an appropriate manner, thus the implementation of other indicators becomes necessary. No certainty can be given to the issue of whether a street is congested or non-congested; the probabilistic nature of this issue makes it a subject of the area of reliability. The reliability of a UTN has direct effects on the sustainability of the city and society. The more reliable network, the less congestion, the less air pollution, the less travel and operation cost, and the more social satisfaction. The performance reliability of a system is defined as the probability that the system under certain conditions during a given time interval functions appropriately [6]. In this article, the performance reliability of a UTN due to RTCs is defined as the probability of traveling in an appropriate manner subject to RTCs condition at a given period of time (e.g. morning peak hour). An appropriate trip from the users' point of view has two characteristics: 1) none of the streets in the users' route is congested and 2) the travel ends in an appropriate time interval. This definition is a combination of connectivity reliability and travel time reliability [7].

By considering different time horizons, various solutions can be suggested to reduce or eliminate congestion (e.g. pricing policy, constructing a new street, street widening, land use management, and urban sprawl policies). In this study, street widening projects are considered as a specific solution. It is assumed that a limited budget is available for street widening, and the objective is to select a set of streets to maximize the performance reliability of UTN subject to RTCs. The performance of a network will be assessed and improved under two different scenarios. In the first scenario, it is assumed that the network's users are not aware of the RTCs in the streets during their trip; hence, their route choosing and changing would not be affected by random congestions in the network. For the second scenario, it is assumed that users are informed about the traffic congestion impulse in the network through different media such as the radio and/or information boards, etc.; which would allow them to change their route based on need and change availability.

Literature review

Considering three different categories, the related literature has been reviewed in this section.

Variability of Travel Time

According to Chen, Zhou [8], the collected traffic data from transportation networks confirms the travel time in the network at a specific hour on different days, is not constant and changes in a random manner. There have been many studies on the changes in travel time, each of which introduces various functions for expressing the travel time density function of networks. Wardrop and Whitehead [9] were the first to address this issue and illustrate the travel time changes on a street suggested an asymmetric distribution. Herman and Lam [10] introduced the Gama and Log-Normal as the closest distribution functions for their observations in the urban streets' travel time changes. Richardson and Taylor [11] deduced that Log-Normal distribution can well explain the changes in travel time in urban streets. Polus [12] found that Gamma distribution can also be applied to illustrate the travel time variations in urban networks. Al-Deek and Emam [13] applied Weibull distribution to determine street travel time changes. Van Lint, Van Zuylen [14] offered different distributions to illustrate the urban streets' travel time changes based on four different traffic conditions. Pu [15] found that the distributions obtained from Van Lint, Van Zuylen [14] are very close to the Log-Normal distribution. Research conducted by Institute [16] indicates that among traditional distributions, Log-Normal distribution is very close to traffic observations.

Assessing the performance reliability of the network subject to RTCs

The reliability of the transportation network's performance has been and is considered a very important issue in recent years. Many researchers have tried to develop indicators for evaluating the reliability of transportation network performance. The focus of this content is on five indexes of the network: connectivity reliability, travel time reliability, behavioral reliability, capacity reliability, and potential reliability of the network [17-19]. Wakabayashi and Iida [20] studied the problem of the reliability of transportation networks' function with respect to RTCs. They considered origin-destination reliability as an index in their study. The reliability of an origin-destination pair was defined as the probability of the existence of at least one route between that origin-destination pair; in a sense, the mentioned route could provide a specific level of service at a given time slot. Al-Deek and Emam [13] evaluated the performance of the network when an incident occurs reducing the capacity of the street(s). Lee, Moon [21] studied the congestion problem and variation in travel time in the network and its effects on the users' behavior. Based on their study, in the real world, the network's travelers tend to continue driving on a route with minimum travel time changes compared to other alternative routes. The probability that the network can shift a certain share of demands at a specified level of service, is studied in the field of network capacity reliability. In this field, most studies have referred to the probability of all network links operating below their capacities, as the capacity reliability index (Al-Deek and Emam [13]; Chen, Kasikitwiwat [22]). Chiou, Liou [23] used the principal component analysis method to model the reliability of travel time in the network. They joined links' travel time data gathered by an electronic toll collection system in order to estimate travel times in each route. They showed that reliability indexes can recognize the unreliable departure time of day for a specific route. Another study analyzing travel time reliability in the network has been conducted by Zhang, He [24]. They considered influential factors on the performance of the network and time reliability. They concluded, link length and left-turn traffic volume could adversely affect the reliability of the links. However, more left-turn streets will improve the reliability of travel time. Lu, Dong [25] considered standstill distance and the following headway as two stochastic parameters and combined them into car-following models in order to predict the travel time reliability in a freeway transportation network.

Identifying and improving critical links

To improve the performance of the urban street networks due to random events, researchers have adopted the identifying and improving critical links approach. A critical link is defined as a link with a great impact on the network's performance, with a high probability of losing functionality when an incident occurs.

Researchers determined the critical link through a simple method, where the importance of each link is calculated by determining the amount of reduction in the reliability of the network as a result of removing that link from the network [26, 27]. Other researchers such as Wang, Liu [28], claimed that sorting based on the significance of the links and removing the most critical ones, would not necessarily have the greatest impact on the reliability of the network performance. They provided an optimization framework for identifying the most critical combination of important links. Bagloee, Sarvi [29] studied the urban transportation network performance by considering disturbances occurring in the network, regardless of type, time, and the source of disruptions. They identified a set of links that the occurrence disruptions on them would lead to the greatest effect on the performance of the network. A two-phase method was presented where in the first phase, the network performance was calculated after the critical links were identified and removed. In the second phase, the performance of the network is calculated by adding the removed links one by one.

Vodák, Bíl [30] developed a deterministic algorithm to find the most crucial links in the network. Their algorithm, instead of searching the whole network, just searches for the shortest cycles. They showed this proposed algorithm can find critical links with significantly less time than traditional algorithms. By taking trip demand and accessibility changes into account, Gecchele, Ceccato [31] evaluated the vulnerability of urban street networks. For this purpose, they used a set of vulnerability indicators to identify vulnerable links in the network. A similar study has been conducted by Cantillo, Macea [32] to evaluate the UTNs' performance against possible disasters. A mathematical model was proposed to find the most critical links in the network to show the best reactions to possible disasters. Tian, She [33] presented an approach to recognize the key links of UTNs due to the temporal-spatial distribution of RTCs. They calculated the traffic congestion for each street, then obtained the time interval of the traffic congestion. Additionally, they used the time interval of traffic congestion as the evaluation criterion to find critical links. Another study aimed to recognize the most critical roads in the UTNs is a study by Guo, Zhou [34]; where the correlation among different locations in the city using real-time traffic data was considered. As the evaluation criteria, they examined the weighted degree and the impact distance in their proposed method.

Although there are some studies in the field of reliability of UTNs, this study has several differences and contributions compared to existing articles. The main contributions are:

- A new performance reliability index is proposed, in consideration of a combination of connectivity reliability and travel time reliability.
- The effects of different levels of users' awareness about RTCs on the reliability of the performance of the network are studied. Two different scenarios are examined for the users' level of awareness; for each scenario, an index is introduced to determine the reliability of the network.
- A bi-level optimization model is developed to evaluate and select street widening projects to maximize the reliability of the network.

Problem definition and assumptions

Network users, due to different reasons, may encounter congested streets on their trips, which would not only lead to dissatisfaction of the users but may also lead to an inappropriate trip.

Definition 1. The route ρ between the node-destination pair (j,s) will be considered as a reasonable route if:

$$\frac{t_{\rho}^{js}}{t^{js}} \leq \theta \tag{1}$$

Where t_{ρ}^{js} is the travel time in route ρ between a node to destination (j,s), t^{js} is the minimum travel time between (j,s), and θ is the user's tolerance threshold concerning the travel time. It is obvious that the number of existing routes in the set of reasonable routes is a non-decreasing function of θ value.

Definition 2. An appropriate route between node-destination (j,s) is a reasonable route, where all of its links are non-congested. According to this definition, a route will be inappropriate if it is either not reasonable or contains at least one congested link.

Definition 3. The network's ability in providing appropriate trips, during a particular time slot (e.g. peak hour) is named the performance of the network subject to traffic congestion.

Definition 4. The performance reliability of the network subject to RTC is the probability of traveling in the network in an appropriate manner is equal to the average number of conducted appropriate trips compared with the total numbers of the conducted trips ratio in the network during a particular time slot (e.g. peak hour).

To improve the reliability of a network subject to RTC, a limited street widening budget is of concern. By assigning this budget, the probability of congestion in selected streets would be reduced and the network performance in providing appropriate routes will improve. Two different scenarios will be considered to evaluate and select the streets for widening. In the first scenario, it is assumed that users traveling in the network are not aware of congestion(s) in the network. Consequently, if a street becomes congested on their route, they would not change their path and their trip would be considered as an inappropriate trip. In the second scenario, it is assumed that the users have full information about the congestion(s) in the network (through different methods like radio, internet, traffic boards, etc.). In this state, if a user becomes aware that there is a congested street ahead and if an alternative appropriate route is available, they will change their route.

Assumption 1. Changing the route because of the congestion(s) has no significant effect on the offered service level to other users, hence their trips remain appropriate**.**

Assumption 2. Congestion would only affect the condition of the users who have already started their trips.

These two assumptions follow the concept of static traffic analysis by evaluating a snapshot of the network condition [35]. For solving the problem mentioned above, it is necessary to determine the percentage of probability of a street becoming congested (or non-congested) at a certain period of time (like peak hour), in an urban transportation network.

Solution Determining the probability of network streets' congestion

Travel time at a specific hour on different days is not the same, because it is affected by various random events. Therefore, different methods are proposed to define the changes in travel time such as Log-Normal density function, probability density function, asymmetric distribution, Weibull distribution, multimodal equilibrium model, connectivity reliability methods, capacity reliability methods, behavioral reliability methods, and potential reliability methods [17, 36]. Log-Normal density function, among the traditional density functions, often better expresses the urban street travel time changes [16]; which is used in this study to describe travel time changes in the network streets. The general formula of the Log-Normal density function with three parameters is as follows:

$$f(x)=\frac{\exp\left(-\frac{\left(\ln\left(\frac{(x-\varpi)}{m}\right)\right)^2}{2\sigma^2}\right)}{(x-\varpi)\sigma\sqrt{2\pi}},\quad x\geq\varpi,\ \ m,\sigma>0 \tag{2}$$

Where, σ is the shape parameter, ϖ is the location parameter and m is the scale parameter. Another form of Log-Normal density function is named the two-variable Log-Normal density function and is as follows:

$$f(x) = \frac{\exp\left(-\frac{\left(\ln\left(\frac{x}{m}\right)\right)^2}{2\sigma^2}\right)}{x\sigma\sqrt{2\pi}}, \quad x \geq 0, \quad m, \sigma > 0 \tag{3}$$

Van Lint, Van Zuylen [14] by gathering traffic data from the urban transportation network, illustrated that the travel time changes in four different conditions: free-flow traffic, congestion onset, congestion, and congestion dissolve. Pu [15] indicated that these observations are very close to the Log-Normal Density function. They calculated the σ value for each one of the above conditions, then estimated the σ value for the free flow as 0.19, the congestion onset as 0.358, the congestion condition as 0.489, and the congestion dissolved as 0.467. Moreover, it is common to use the following equations for the *m* parameter value in the two-variable Log-Normal density function:

$$t_{mean} = m \exp(0,5\sigma^2) \tag{4}$$

$$t_{median} = m \tag{5}$$

The question here is whether it is possible to calculate the congestion probability of a street, provided the free-flow travel time and the mean travel time of that street are available. To answer this question, a simple assumption in modeling t_{median} is assumed. According to the definition, t_{median} for a street in a given traffic condition is the time duration where 50% of entering vehicles pass in less than the assumed time duration. Given the definition of t_{median}, it is clear that t_{median} value of a street is related to the free travel time of that street (t_0) and its congestion volume in those given traffic conditions (t_{mean} / t_0). Consequently, a simple model can be proposed for obtaining t_{median} as follows:

$$t_{median} = t_0 \left(\frac{t_{mean}}{t_0}\right)^{\alpha} \tag{6}$$

Where α is a parameter which should be estimated. Replacing Eq. 6 into Eq. 4 results:

$$t_{mean} = t_{median} \exp(0,5\sigma^2) = t_0 \left(\frac{t_{mean}}{t_0}\right)^{\alpha} \exp(0,5\sigma^2) \tag{7}$$

$$\Rightarrow \left(\frac{t_{mean}}{t_0}\right)^{1-\alpha} = \exp(0,5\sigma^2) \tag{8}$$

Based on Pu [15] σ is considered equal to 0.489 for the moment of congestion and it's assumed that the congestion in a street occurs when ${t_{mean}}/{t_0} > 2$, thus α value can be estimated as 0.82 from Eq. 8, therefore, σ value for a street can be calculated as follows:

$$\sigma = \sqrt{2\ln\left(\left(\frac{t_{mean}}{t_0}\right)^{0.18}\right)} \tag{9}$$

Using Eq. 3 and Eq. 8the travel time density function can be calculated. Also based on the probability's laws:

$$p(\hat{t}) = \int_0^{\hat{t}} f(t)dt \tag{10}$$

Where $p(\hat{t})$ is the probability that travel time in the intended street is less than $\hat{t}$. In order to determine the probability of congestion in the street, $1-p(2t_0)$ should be calculated. Likewise, to determine the probability of a street being non-congested, calculating $p(2t_0)$ value is needed (see Fig. 1).

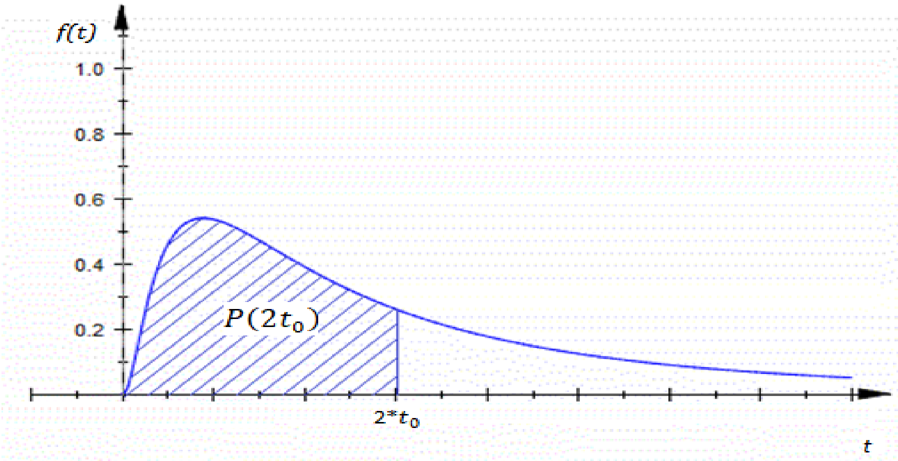

Fig. 1. Log-Normal curve diagram

Determining a reliability index to evaluate the performance of the network when RTC occurs, and users are not aware

The users of the UTNs often choose the shortest paths among the accessible routes set, based on their past experiences. If users are not provided with new information regarding the network's condition during their trip, they will use their daily route to reach their destination. Hence, when there is congestion in some of the streets on their route, their trip will become inappropriate. Assume the set of the shortest routes between node-destination (j,s) is named ρ^{js}. If the user is on the link (i,j) at the present time and intends to move from node j to destination s through route ρ ($\rho \in \rho^{js}$), the probability of reaching destination s through this route in the appropriate manner is $P_{ij} \times P_1(\rho)$, where P_{ij} is the probability of link (i,j) to be non-congested and $P_1(\rho)$ is the probability of route ρ being non-congested. According to this relation, the network performance reliability under RTC occurrence when users are not aware of traffic conditions can be determined as follows:

$$R = \frac{\sum_{s\in D}\sum_{j\in V}\sum_{\rho\in\rho^{js}}\sum_{i\in B(j)}\varphi^{s}_{ij,p}\times P_{ij}\times P_1(\rho)}{\sum_{(k,s)\in W} d^{ks}} \tag{11}$$

Where $\varphi^{s}_{ij,p}$ is the number of users on the link (i, j) who are intended to travel to the destination s through the route ρ $(\rho\in\rho^{js})$. d^{ks} is the travel demand from k to s, $B(j)$ is the set of links by the end on node j, ρ^{js} is the set of shortest paths between (j,s). V is the network nodes set, D is the network destinations set and W is the network origin-destinations set. $\varphi^{s}_{ij,p}$ is obtained as:

$$\varphi^{s}_{ij,p} = \sum_{k\in O} d^{ks}_{ij,\rho}\times\left(\frac{t_{ij}}{t^{ks}}\right),\qquad i\in B(j),\ \rho\in\rho^{js} \tag{12}$$

Where $d^{ks}_{ij,\rho}$ is the travel demand from origin k to destination s, which passes through the link (i, j) and take the path ρ between node-destination (j,s) to reach destination s. t_{ij} is the travel time on the link (i, j), t^{ks} is the travel time from origin k to destination s and O is the network origins set. It should be mention that $\left(t_{ij}/t^{ks}\right)$ indicates the share of the link (i, j) of that path hosting these travelers at that instance. In this study, a non-congested route is defined as a route where all of its links are non-congested; by assuming the probability of the network links being non-congested is independent, therefore, $P_1(\rho)$ can be obtained as [37]:

$$P_1(\rho) = \Pi_{(l,m)\in A} P_{lm}\delta^{js}_{lm,\rho} \tag{13}$$

Where P_{lm} is the probability of link (l,m) to be non-congested, A is the set of the network links and $\delta^{js}_{lm,\rho}$ is a binary parameter equal to 1 if link (l,m) belongs to $\rho\in\rho^{js}$, otherwise, it is 0.

Determining a reliability index to evaluate the performance of the network when RTC occurs and users are aware

In this scenario, it is assumed the users are aware of the network streets congestion during their trip. In this situation, they can be divided into three groups: 1) users who have become aware there is congestion ahead of their route. Logically, these users would change their path at the first node, allowing them to have access to an appropriate alternative route. 2) Users who do not have access to an appropriate alternative route and have to finish their trip inappropriately. 3) Users who are entrapped in the congested streets and have no choice but to pass through congested streets leading to an inappropriate trip. In this scenario, the reliability of the network will be obtained as follows:

$$R = \frac{\sum_{s\in D}\sum_{j\in V}\varphi^{js}\times P_2(rp^{js})}{\sum_{(k,s)\in W} d^{ks}} \tag{14}$$

Where φ^{js} is the number of users who are on links that end at node *j*, while their objective is to reach destination *s* and approach *j* without experiencing any congestion. rp^{js} is the set of reasonable paths between (j,s) and $P_2(rp^{js})$ is the probability of the existence of at least one appropriate route among the reasonable routes set between (j,s) (i.e. reliability of the node-destination (j,s)). φ^{js} is obtained as follows (symbols are similar to Eq. 12):

$$\varphi^{js} = \sum_{k\in O}\sum_{\rho\in\rho^{js}}\sum_{i\in B(j)} d_{ij,\rho}^{ks}\times P_{ij}\times\left(\frac{t_{ij}}{t^{ks}}\right) \tag{15}$$

Based on definition 1, having users' tolerance threshold value (θ), it will be easy to determine the reasonable routes set between node-destination (j,s). The probability of an appropriate trip between node-destination (j,s) can be determined as follows:

$$\begin{aligned} P_2(rp^{js}) = &\sum_{x=1}^{n} P(rp_x^{js}) - \sum_{1<x<y\le n}^{n} P(rp_x^{js}\cap rp_y^{js}) + \sum_{1<x<y<z\le n}^{n} P(rp_x^{js}\cap rp_y^{js}\cap rp_z^{js}) \\ &- ... + (-1)^{n+1}\, p(rp_1^{js}\cap rp_2^{js}\cap ...\cap rp_n^{js}) \end{aligned} \tag{16}$$

Where rp_x^{js} is the x^th^ route in rp^{js} set, *n* is the size of rp^{js}. $P(rp_x^{js})$ is the probability of the path rp_x^{js} to be non-congested, calculated through Eq. 17:

$$P(rp_x^{js}) = \prod_{(l,m)\in A} P_{lm}\delta_{lm,x}^{js} \tag{17}$$

Where P_{lm} is the probability of the link (l,m) being non-congested, *A* is the network links set. $\delta_{lm,x}^{js}$ is a binary parameter equal to one if the link (l,m) belongs to the path *x* of the node-destination (j,s), otherwise, it is zero.

Calculating $P_2(rp^{js})$ through Eq. 16 is very time-consuming. Due to the higher number of reasonable routes, the higher calculation time in an exponential sense. The origin-destination reliability problem is an Np-hard problem [38] and its calculation becomes complicated when the number of reasonable routes is high. Therefore, to deal with this issue many approximate methods have been suggested [39]. [40] used a method estimating the upper bound through the minimum path set. [41] used a different method estimating lower bounds through minimum cuts set. [42] applied a method that entails polynomial algorithms for finding useful subclasses of the network. Additionally, the Monte-Carlo simulation method is applied to address this problem [43, 44]. In this study, an innovative method is presented to determine the reliability of the urban transportation network performance subject to recurrent congestion(s). Based on Eq. 14, the reliability of the network performance (*R*) can be expressed in an equation in accordance with the weighted summation of reliability of the performance of the network's node-destinations as follows:

$$R \approx \sum_{(j,s)\in Z} \varphi^{js}\times P_2(rp^{js}) \tag{18}$$

Where *Z* is the nodes-destinations set. The reliability of the performance of (j,s) depends on φ^{js} which is obtained through Eq. 15. φ^{js} is an upward function of the number of users reaching node j with the intention of traveling to destination s. Because distance (travel time) is a dissuasive factor in urban transportation trips, there is usually less demand for traveling to distant points. Therefore, if the distance between node-destination (j,s) is long, the amount of φ^{js} will be low and it is not necessary to calculate the exact value of $P_2(rp^{js})$. If the distance between node-destination (j,s) is short, φ^{js} might be high and an exact calculation of $P_2(rp^{js})$ is required. According to definition (1) and closeness of node-destination (j,s), the number of reasonable routes between this node-destination would not be high; thus, making an exact calculation of $P_2(rp^{js})$ at a short period of time possible. To calculate $P_2(rp^{js})$, to obtain the reliability of the performance of the node-destinations, two methods are adopted. First, for node-destinations close to each other, an exact method is applied to calculate the reliability of the network performance, similar to applying Eq. 16. Second, for node destinations that are far from each other, an approximate method is applied. The Monte-Carlo simulation method is adopted to calculate the reliability of long-distance node-destination performance. The Monte-Carlo simulation is a method used for calculating the probability problems through which analytical methods are impossible or very time-consuming [45]. The simplicity of this method and its capacity in fully considering the correlation between reasonable paths of a node-destination in the transportation networks are two main advantages of adopting this method.

Case Improving the reliability of network performance subject to RTC

In this section, a bi-level model is presented to improve the reliability of network performance due to RTC. The assumptions made in this model are based on budget limitations, limiting the number of the candidate streets selected to be widened. The cost of each widening project is predetermined. The proposed bi-level optimization model is as follows:

Upper-Level model:

$$Max\ R \qquad s.t \tag{19}$$

$$\sum_{a\in\bar{A}} c_a z_a \le B \tag{20}$$

Lower-Level model:

$$Min \quad \sum_{a\in A}\int_0^{v_a} t_a(x)dx + \sum_{a\in\bar{A}} z_a \int_0^{v_a} (t'_a(x) - t_a(x))dx \qquad s.t \tag{21}$$

$$\sum_{\rho\in\rho^{ks}} x_\rho^{ks} = d^{ks} \qquad \forall (k,s)\in\rho \tag{22}$$

$$v_a = \sum_{(k,s)\in\rho}\sum_{\rho\in\rho^{ks}} \delta_{a,\rho}^{ks} x_\rho^{ks} \qquad \forall a\in A \tag{23}$$

$$x_\rho^{ks} \ge 0,\ \forall \rho\in\rho^{ks}, (k,s)\in p \tag{24}$$

Where R is the reliability indicator for network performance subject to RTC, A is the network links set, and $\bar{A}$ is the candidate links set for street widening. B is the total available budget for street widening, c_a is the widening cost of the link a $(a\in\bar{A})$, $t_a(v_a)$ is the travel time-volume function of link a $(a\in A)$, and $t'_a(v_a)$ is the travel time-volume function of the link a $(a\in\bar{A})$ if street widening is performed on it. To provide a better view of the methodology, Fig. 2 presents the flowchart of the method and procedure.

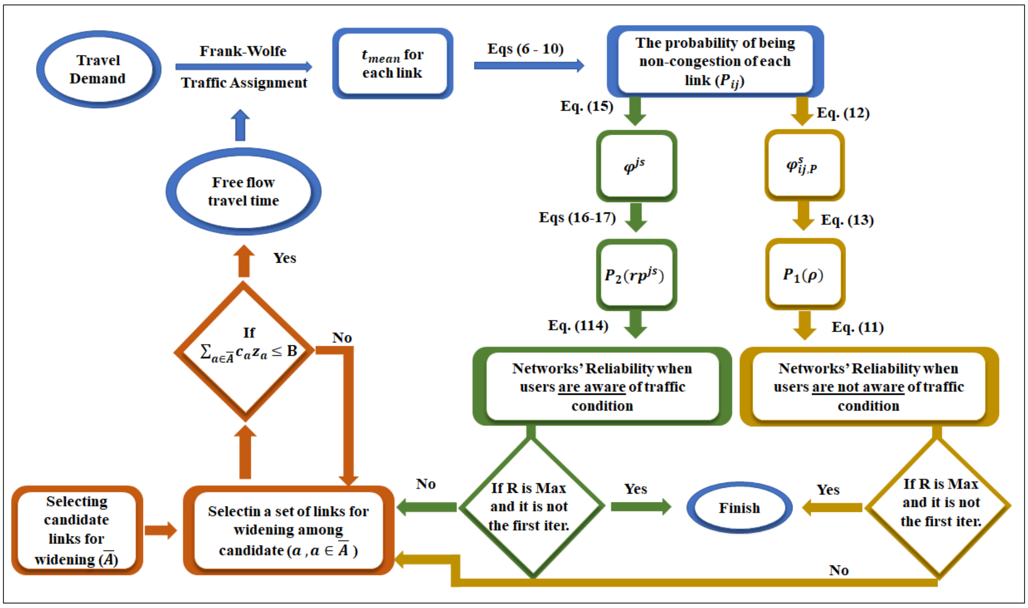

Fig. 2. Flowchart of the applied method and modeling procedure

Selecting streets for widening is a network design problem. This problem is Np-hard, in which an increase in dimensions of the problem increases its solving time exponentially [3]. To solve these problems in large dimensions, many researchers have used metaheuristic methods [46]. In this study, a Quantum-inspired evolutionary algorithm (QIEA) is applied to solve this problem. QIEA is a population-based metaheuristic method inspired by quantum mechanics concepts and improves the process of searching and optimizing evolutionary methods. Evolution algorithms are of random search types inspired by Darwinian evolutionary theory. These algorithms provide better results in comparison with other optimization methods, similar to gradient-based methods, in solving problems with multiple local optimal answers [47-49]. The QIEA was first proposed by Narayanan and Moore in 1996 to solve the traveling salesman problem [50], but it was not in full focus until several years later in 2000-2002, an applied algorithm of this method was proposed [51, 52]. Although various types of this algorithm have been introduced since then, the algorithm's main structure has not changed and follows its initial form Zhang [53]. In this kind of algorithm, an initial population of the answer set is encoded and generated through Q-bits to fit within the problem constraints. If it is rejected, the generated population will be corrected by removing the rejected Q-bit. Afterwards, by applying the Q-gate and the Quantum rotation gate the answer set will be updated and converted from one generation to the next. This process continues until the stop condition is met, this condition is the convergence of the modified response population (for more details see Mani and Mani [49]). In this study, a specific number of iterations is considered as the stop condition. For more information regarding the QIEA and the validation of this method please see [54].

Numerical example

In order to evaluate the accuracy of the proposed models mentioned in this paper and illustrate their operational capability in real transportation networks, this method is implemented on the Sioux Falls network (Fig. 3). The Sioux Falls network is a part of South Dakota, United States, transportation network consisting of 24 nodes and 76 links and is applied in many transportation studies. The travel time-volume function of link $(i, j) \in A$ in this network is presented as $t_{ij} = \alpha_{ij} + \beta_{ij} v_{ij}^4$, where, t_{ij} is the mean travel time in the link (i, j). v_{ij} is the traffic flow passing through the link (i, j), α_{ij} is the free flow travel time (indicated by t_0), and β_{ij} is the congestion parameter of the link (i, j). The transportation details of this network are tabulated in Table 1. This information includes t_0, the congestion parameter of each link (β), and the congestion parameter after widening (β'). Moreover, the details of the origin-destination demand matrix (d^{ks}) of this network are tabulated in Table 2.

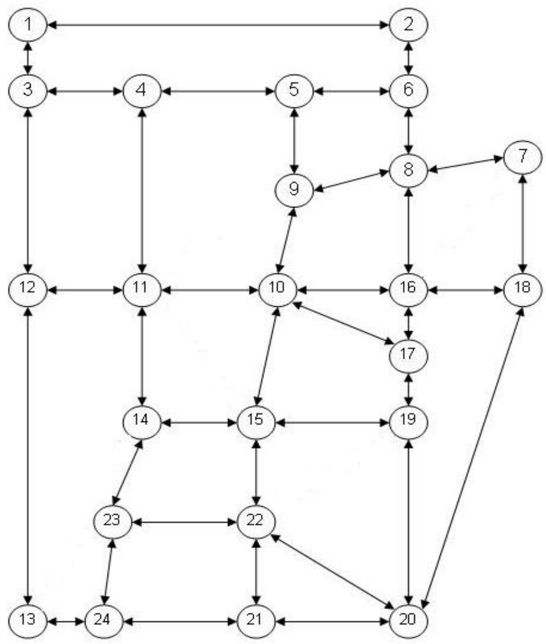

Fig. 3. Sioux falls transportation network

Table 1. Specification of links of Sioux Falls network

Link (i,j)	t_0 ($\times 10^{-2}hr$)	β^*	β'^{**}	**Link** (i,j)	t_0 ($\times 10^{-2}hr$)	β^*	β'^{**}
(1,2)	5.96	6.13	1.00	(11,12)	6.46	5.38	0.45
(1,3)	4.34	4.52	1.00	(11,14)	4.42	10.4	0.25
(2,6)	5.17	8.29	0.77	(12,13)	2.98	9.96	1
(3,4)	4.31	5.04	0.99	(13,24)	3.72	3.07	0.16
(3,12)	4.14	4.35	1.00	(14,15)	4.52	7.99	0.32
(4,5)	2.16	2.95	0.90	(15,19)	3.50	5.04	0.80
(4,11)	6.46	9.5	0.84	(15,22)	3.50	11.28	0.37
(5,6)	4.17	9.95	0.48	(16,17)	1.67	10.07	0.16
(5,9)	5.03	13.54	0.42	(16,18)	2.69	9.35	0.99
(6,8)	2.17	2.42	0.09	(17,19)	2.31	4.67	0.31
(7,8)	2.50	19.1	0.36	(18,20)	4.46	14.28	0.99
(7,18)	2.18	12.59	0.99	(19,20)	3.99	14.80	0.39
(8,9)	9.61	14.89	0.60	(20,21)	5.72	10.48	0.69
(8,16)	4.82	16.41	0.43	(20,22)	4.71	4.36	0.60
(9,10)	2.75	19.62	0.47	(21,22)	1.67	6.73	0.40
(10,11)	5.00	16.62	0.37	(21,24)	3.29	20.97	0.24
(10,15)	5.87	18.35	0.40	(22,23)	4.00	22.14	0.29
(10,16)	4.50	3.21	0.19	(14,23)	4.25	7.25	0.46
(10,17)	8.04	15.02	0.47	(23,24)	1.88	24.08	0.50

* $\beta\ 10^{-4} \times hr(1000veh/day)^4$ ** $\beta'\ 10^{-4} \times hr(1000veh/day)^4$

Table 2. O/D Travel demand for Sioux falls network (thousands of veh/day) *

O-D	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	0	0.3	0.3	1.2	0.5	0.7	1	1.7	1.2	2.7	1.2	0.5	1.1	0.6	1	1.2	0.9	0.3	0.6	0.6	0.3	0.8	0.6	0.3
2	0.2	0	0.3	0.5	0.3	1	0.5	0.9	0.5	1.2	0.5	0.4	0.7	0.2	0.3	0.9	0.5	0.1	0.3	0.3	0.2	0.3	0.2	0.1
3	0.3	0.3	0	0.6	0.2	0.7	0.2	0.5	0.3	0.7	0.7	0.5	0.4	0.3	0.2	0.5	0.3	0.1	0.1	0.2	0.1	0.3	0.2	0.2
4	1.2	0.5	0.6	0	1	1	1	1.4	1.5	2.5	3	1.4	1.2	1.1	1	1.6	1.1	0.3	0.5	0.8	0.5	0.9	1	0.5
5	0.5	0.3	0.2	1	0	0.6	0.5	1.2	1.7	2.1	1.1	0.5	0.4	0.4	0.6	1.1	0.6	0.1	0.3	0.4	0.2	0.5	0.3	0.2
6	0.7	1	0.7	1	0.6	0	0.8	1.7	0.9	1.6	0.9	0.6	0.5	0.3	0.5	2	1.1	0.2	0.6	0.7	0.3	0.6	0.3	0.2
7	1	0.5	0.3	0.9	0.5	0.8	0	2.1	1.2	3.8	1.1	1.5	0.9	0.6	1.1	2.9	2.1	0.4	0.9	1.2	0.6	1.1	0.5	0.3
8	1.7	0.9	0.5	1.4	1.2	1.7	2.1	0	1.7	3.3	1.8	1.3	1.3	0.8	1.3	4.5	2.8	0.6	1.5	1.9	0.8	1.2	0.8	0.5
9	1.2	0.5	0.4	1.5	1.7	0.9	1.2	1.7	0	5.7	2.9	1.3	1.2	1.2	2	3	1.9	0.4	1	1.4	0.7	1.5	1.1	0.5
10	2.7	1.2	0.7	2.5	2.1	1.6	3.8	3.3	5.7	0	8.1	4.1	3.9	4.3	8.1	8.9	7.9	1.4	3.7	5.1	2.6	5.4	3.7	1.7
11	1.2	0.5	0.6	3	1.1	0.9	1.1	1.8	2.9	8	0	2.9	2.1	3.2	2.9	2.9	2.1	0.4	1	1.4	0.9	2.3	2.7	1.2
12	0.5	0.4	0.5	1.4	0.5	0.6	1.5	1.3	1.3	4.1	2.9	0	2.8	1.4	1.6	1.4	1.3	0.5	0.7	1	0.8	1.5	1.5	1.1
13	1.1	0.7	0.4	1.2	0.4	0.5	0.9	1.3	1.2	3.8	2.1	2.8	0	1.3	1.5	1.3	1.2	0.2	0.7	1.4	1.3	2.6	1.7	1.6
14	0.6	0.2	0.2	1.1	0.4	0.3	0.6	0.8	1.2	4.3	3.2	1.4	1.3	0	2.7	1.4	1.4	0.3	0.7	1	0.9	2.5	2.2	0.9
15	1	0.3	0.2	1	0.5	0.5	1.1	1.3	2	8.1	2.9	1.5	1.5	2.7	0	2.5	3.1	0.5	1.7	2.2	1.7	5.2	2	0.9
16	1.2	0.9	0.5	1.6	1.1	2	2.9	4.5	3	8.9	2.9	1.4	1.3	1.4	2.5	0	5.7	1	2.7	3.4	1.3	2.5	1.1	0.7
17	0.9	0.5	0.3	1.1	0.6	1.1	2.1	2.8	1.9	7.8	2.1	1.3	1.2	1.4	3.1	5.7	0	1.3	3.5	3.5	1.3	3.5	1.3	0.6
18	0.3	0.1	0.1	0.3	0.1	0.2	0.4	0.6	0.4	1.4	0.4	0.5	0.2	0.2	0.5	1	1.3	0	0.7	0.9	0.3	0.7	0.2	0.1
19	0.6	0.3	0.1	0.5	0.3	0.6	0.9	1.5	1	3.7	1	0.7	0.7	0.7	1.7	2.7	3.5	0.7	0	2.5	0.9	2.5	0.8	0.4
20	0.6	0.3	0.2	0.8	0.4	0.7	1.2	1.9	1.4	5.1	1.4	1	1.4	1	2.2	3.4	3.5	0.9	2.5	0	2.5	5	1.4	1
21	0.3	0.2	0.1	0.4	0.2	0.3	0.6	0.8	0.7	2.6	0.9	0.8	1.3	0.9	1.7	1.3	1.3	0.3	0.9	2.5	0	3.7	1.5	1.2
22	0.8	0.3	0.3	0.9	0.5	0.6	1.1	1.2	1.5	5.4	2.3	1.5	2.6	2.5	5.2	2.5	3.5	0.7	2.5	5	3.7	0	4.4	2.4
23	0.6	0.2	0.3	1	0.3	0.3	0.5	0.8	1.1	3.7	2.7	1.5	1.7	2.2	2	1.1	1.3	0.2	0.8	1.4	1.5	4.4	0	1.6
24	0.3	0.1	0.2	0.5	0.2	0.2	0.3	0.5	0.5	1.7	1.2	1.1	1.6	0.9	0.9	0.7	0.6	0.1	0.4	1	1.2	2.4	1.5	0

* The demand values should be divided by 2 and then used

Determining the reliability of performance of Sioux Falls network due to RTC

To determine the reliability of network performance (R) subject to the RTC in both scenarios, the following steps have been taken:

Step 1. A travel demand matrix is assigned to the network concerning the Sioux Falls network and t_{mean} for each link is obtained. Table 3 shows t_{mean} values for each link.

Step 2. The probability of non-congestion of each link (P_{ij}) is obtained by inserting the values of t_0 and t_{mean} in Eqs. 6 - 10. The values of P_{ij} for each link are tabulated in Table 3.

Step 3. Using Eqs. 12 and 15 the values of $\varphi^{s}_{ij,\rho}$ and φ^{js} are obtained respectively.

Step 4. $P_1(\rho)$ and $P_2(rp^{js})$ are calculated. $P_1(\rho)$ is calculated through Eq. 13. To calculate $P_2(rp^{js})$, at first, a set of reasonable routes between each node-destination should be obtained based on the tolerance threshold of users. In this example, the tolerance threshold of users (θ) is assumed as 1.5. Accordingly, the set of reasonable routes between each node destination is obtained. For node-destination pairs with a number of reasonable routes less than 15, Eqs. 16 and 17 are used to calculate the probability of existing at least one appropriate route between that node-destination. As it is hard to do calculations with ordinary computers, to calculate $P_2(rp^{js})$, if the number exceeds 15, the Monte-Carlo simulation method is applied with 1000 iteration.

Step 5. The value of R is calculated for both scenarios, using. (11) and (14) (Table 4).

Table 3. Free flow travel time, mean travel time, and non-congestion probability of links

Link (i,j)	$t_0(\times 10^{-2}\,hr)$	$t_{mean}(\times 10^{-2}\,hr)$	P_{ij}	Link (i,j)	$t_0(\times 10^{-2}\,hr)$	$t_{mean}(\times 10^{-2}\,hr)$	P_{ij}
(1,2)	5.96	6.13	1	(11,12)	6.46	5.38	0.45
(1,3)	4.34	4.52	1	(11,14)	4.42	10.4	0.25
(2,6)	5.17	8.29	0.77	(12,13)	2.98	9.96	1
(3,4)	4.31	5.04	0.99	(13,24)	3.72	3.07	0.16
(3,12)	4.14	4.35	1	(14,15)	4.52	7.99	0.32
(4,5)	2.16	2.95	0.90	(15,19)	3.50	5.04	0.80
(4,11)	6.46	9.5	0.84	(15,22)	3.50	11.28	0.37
(5,6)	4.17	9.95	0.48	(16,17)	1.67	10.07	0.16
(5,9)	5.03	13.54	0.42	(16,18)	2.69	9.35	0.99
(6,8)	2.17	2.42	0.09	(17,19)	2.31	4.67	0.31
(7,8)	2.50	19.1	0.36	(18,20)	4.46	14.28	0.99
(7,18)	2.18	12.59	0.99	(19,20)	3.99	14.80	0.39
(8,9)	9.61	14.89	0.60	(20,21)	5.72	10.48	0.69
(8,16)	4.82	16.41	0.43	(20,22)	4.71	4.36	0.60
(9,10)	2.75	19.62	0.47	(21,22)	1.67	6.73	0.40
(10,11)	5.00	16.62	0.37	(21,24)	3.29	20.97	0.24
(10,15)	5.87	18.35	0.40	(22,23)	4.00	22.14	0.29
(10,16)	4.50	3.21	0.19	(14,23)	4.25	7.25	0.46
(10,17)	8.04	15.02	0.47	(23,24)	1.88	24.08	0.50

Table 4. Result of calculating reliability

Reliability index	**Non-awareness**	**Full awareness**
R	0.3708	0.3920

Prior to street widening indicated in Table 4, 37.08% of in-progress trips on the Sioux Falls network, in the case of non-awareness, will be appropriate; the same holds at 39.20% in full awareness. In other words, the awareness of the users will improve the reliability of network performance by up to 2.12%. The question arises as to whether the amount of impact of awareness regarding congestion conditions on the reliability of the network's performance is influenced by traffic congestion in the network. The results of assigning nine different traffic demand patterns to the Sioux Falls network in terms of the impact of awareness on the network congestion condition, on the reliability of Sioux Falls network performance is tabulated in Table 5. Naturally, by changing travel demand in the network, traffic flow crossing through links and probability of non-congestion in the network's links will change.

Table 5. Results of assigning nine different demands on the Sioux falls network

Total travel demand	**Reliability value (non-awareness)**	**Reliability value (full awareness)**	**Differences**
$\boldsymbol{d^{ks}}$	0.0496	0.0499	0.0003
66% of $\boldsymbol{d^{ks}}$	0.1765	0.1797	0.0032
50% of $\boldsymbol{d^{ks}}$	0.3708	0.3920	0.0212
40% of $\boldsymbol{d^{ks}}$	0.5810	0.6203	0.0393
33% of $\boldsymbol{d^{ks}}$	0.7420	0.7800	0.0380
28% of $\boldsymbol{d^{ks}}$	0.8398	0.8700	0.0302
25% of $\boldsymbol{d^{ks}}$	0.8955	0.9188	0.0233
22% of $\boldsymbol{d^{ks}}$	0.9260	0.9454	0.0194
20% of $\boldsymbol{d^{ks}}$	0.9438	0.9583	0.0145

As observed in Table 5, the awareness effect on improving the reliability of the network performance is associated with congestion, and its distribution diagram is presented in Fig. 3.

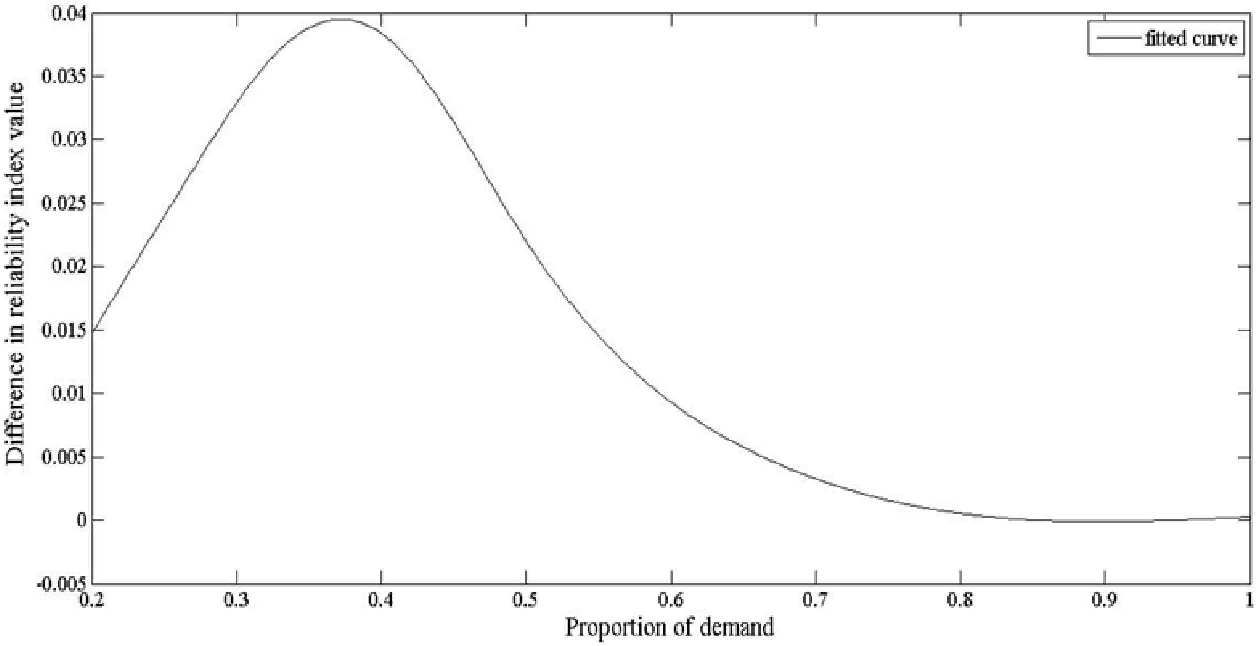

Fig. 4. Distribution of the impact of network crowding on increasing the reliability of network performance by providing information about traffic conditions to the users

The following points can be pointed out in Table 5 and Fig. 4:

- The effect of users' awareness of the network traffic condition on improving the reliability of network performance in very congested networks is not high. This can be because in the congested networks all links are congested, therefore, the probability of an appropriate alternative route existing between node-destinations of the network is very low.
- In non-congested networks, detouring is not necessary. Consequently, users' awareness will increase the reliability of the network performance, more than those of congested networks.
- The biggest effect of users' awareness through the network to improve the reliability of network performance, is related to the condition where the network is half-congested. In this case, some of the network links are congested, and informing drivers about the congestion of those links, with the existence of appropriate alternative routes, can improve the reliability of the network more than in other cases.

Improve the performance of Sioux Falls Network through street widening approach

Adding a line to a street will increase the width of said street. It is assumed there is a limited budget for street widening for some of the Sioux Falls network's streets. The objective is to identify the streets on the network in which widening, would lead to maximizing the reliability of the network. To this end, the proposed bi-level optimizing model should be solved. Applying a full enumeration algorithm for the Sioux Falls network, 2^{76} links sets should be assessed to identify optimal links set for street widening. A logical approach is where non-congested streets or streets whose non-congestion probability is close to 1, cannot be selected as members of candidate links. By considering the probability values of the Sioux Falls network's links in Table 3, 20 links with less probability of non-congestion are selected as candidate links for street widening. Through this approach, 2^{76} will be reduced to 2^{20}. Table 6 shows the candidate links and related widening costs. To make these costs rational, the street widening costs are considered proportional to the free-flow travel time of each link. In addition, B=20 money units are assumed. Solving the bi-level optimization model through a full enumeration algorithm, optimal links are selected for street widening (Table 7). As it is clear from Table 7, the reliability index in the first and second scenarios would be upgraded from 0.3778 to 0.5703 and from 0.3920 to 0.6103, respectively.

Table 6. Non-congestion probability and street widening cost of candidate links

Link (*i*,*j*)	P_{ij}	Widening cost	Link (*i*,*j*)	P_{ij}	Widening cost
(6.8)	0.09	2.17	(11,14)	0.25	4.42
(16,17)	0.16	1.76	(22,23)	0.29	4.00
(13,24)	0.16	3.72	(17,19)	0.31	2.31
(10,16)	0.19	4.50	(14,15)	0.32	4.52
(21,24)	0.24	3.29	(10,11)	0.37	5.00

Table 7. Selected links for street widening

Link (*i*,*j*)	Users are non-awareness	Users are full awareness	Link (*i*,*j*)	Users are non-awareness	Users are full awareness
(6.8)	*	*	(11,14)		
(8,6)	*	*	(14,11)		
(16,17)	*	*	(22,23)		
(17,16)	*	*	(23,22)		
(13,24)			(17,19)	*	
(24,13)			(19,17)		*
(10,16)	*	*	(14,15)		
(16,10)	*	*	(15,14)		
(21,24)			(10,11)		
(24,21)			(11,10)		

Analyzing Table 7 can make some interesting findings. 1) The combination of links most likely to be congested, is not considered for street widening. Here, mere congestion of the links is not a factor in selecting them for street widening. 2) The selected links for street widening in both scenarios are similar, this similarity does not prevail in generality. To illustrate this expression, Table 8 indicates the number of selecting each link as the optimal link for widening in the assigned nine different travel demand matrices. As Table 8 shows, the central-located links of the Sioux Falls network are the ones most frequently selected.

Table 8. The number of selecting each link as the optimal link in nine different demand conditions

Link (*i*,*j*)	Chosen for street widening without information	Chosen for street widening with full information	Total	Link (*i*,*j*)	Chosen for street widening without information	Chosen for street widening with full information	Total
(6.8)	6	4	10	(11,14)	2	1	3
(8,6)	6	7	13	(14,11)	2	1	3
(16,17)	9	7	16	(22,23)	0	0	0
(17,16)	8	8	16	(23,22)	0	1	1
(13,24)	1	0	1	(17,19)	4	6	10
(24,13)	0	1	1	(19,17)	3	4	7
(10,16)	8	9	17	(14,15)	0	0	0
(16,10)	8	9	17	(15,14)	0	0	0
(21,24)	1	0	1	(10,11)	0	0	0
(24,21)	0	0	0	(11,10)	0	0	0

Optimizing network performance reliability subject to both scenarios in the Sioux Falls network, a medium-sized transportation network, through a full enumeration algorithm is time-consuming. As discussed in the previous section, to accelerate solving this problem, the QIEA is applied. To make the answers obtained from QIEA attributive and accurate, tuning the parameters of the algorithm is necessary. Therefore, by applying the full factorial design, the parameters are tuned, and the results indicate 100 iterations values and 30 generated populations of each iteration. By applying QIEA, the time used for solving the bi-level optimization model of reliability index applied on the Sioux Falls network is reduced from an average amount of 400 minutes, in full enumeration algorithm to 45 minutes through a computer with 2.40 GHz CPU and 4 GB RAM.

Discussion and conclusion

The stability and sustainability of street networks concerning the usual and unusual traffic congestion occurrence are one of the issues that have become a major focus in transportation studies. Changes in travel demand at a particular hour of the day and changes in streets' capacity due to various reasons lead to traffic congestion in Urban Transportation Networks, UNTs, in a random manner, known as Recurrent Traffic Congestions, RTCs.

One of the objectives of this study was to evaluate the performance of UTNs subject to RTCs. These types of congestions follow a random pattern, hence to assess the network's performance a reliability measure is proposed, considering two major concepts in transportation network analysis, which are connectivity reliability and travel time reliability. In this context, the reliability of network performance is defined as the probability of traveling in the network in an appropriate manner; which is equal to the average number of appropriate trips conducted versus the total trips conducted in the network. Moreover, an appropriate trip for users is a trip where users do not encounter any congested street and end the trip at a reasonable time. Moreover, the current study considered two different scenarios in defining the reliability of the network. In the first scenario, it is assumed the users traveling on the network, are not aware of the network traffic congestion(s) and take their daily route to their destination. In the second scenario, it is assumed the users are aware of network traffic congestion(s) during their trip and change their route if an appropriate alternative route exists in case of congestion occurs on their path. Due to the complexity of calculating the network's reliability when users' are provided with traffic information, a new method is introduced in determining the reliability of the network in the second scenario. This study first, assessed the effect of providing traffic information to network users on network reliability. Results showed that users' awareness of the network traffic condition could only increase the reliability of network performance in networks with low demands. In congested networks, providing traffic information to the users will not be helpful to increase the network's reliability and other methods of traffic management are needed.

Another objective of this study was to apply street widening projects to maximize the network's performance reliability. Considering financial limits, a bi-level urban transportation network design model is developed to indicate a set of links for street widening. To analyze the performance of the proposed model and demonstrate its practicality on transportation networks, the model is implemented on the Sioux Falls network subject to both conditions of non-awareness and awareness of users. The results indicate congested streets, central-located links, are more likely to be selected for street widening. The results of this paper are in line with Wang, Liu [28], which mentioned that sorting and selecting only congested links for the street widening is not always the best solution in improving networks reliability.

Taking into account street widening is a network design and an Np-Hard problem, to reduce its solving time two techniques are applied. 1) Due to logical reasoning, non-congested streets were not considered as candidate links. 2) QIEA is applied instead of the exact methods such as full enumeration algorithm, to maintain accuracy and reduce problem-solving time to a great extent.

There are research directions for future studies mentioned. In this study, all parameters are considered in deterministic form, to make the problem more realistic the future studies can consider the uncertainty of the parameters. As a second suggestion, a new index can be developed to evaluate the reliability of the network. Thirdly, future studies with access to real data can apply the proposed model to evaluate the performance of real large scale UTNs. Although this study sheds light on the reliable transportation network design problem with two different scenarios considered; future studies can take the combination of these scenarios as a third scenario. Finally, other heuristic/metaheuristic algorithms can be applied to solve large-scale problems using the proposed model and compare results.

References

[1] Khayamim, R., et al., *A sustainable approach for selecting and timing the urban transportation infrastructure projects in large-scale networks: A case study of Isfahan, Iran.* Sustainable Cities and Society, 2020. 53: p. 101981.

[2] Mahmoudi, R., et al., *Determining the relative importance of sustainability evaluation criteria of urban transportation network.* Sustainable Cities and Society, 2019. 47: p. 101493.

[3] Mahmoudi, R.S., Nader; Hejazi, Reza; Emrouznejad, Ali; Rajabi, Parisa;, *A hybrid egalitarian bargaining game-DEA and sustainable network design approach for evaluating, selecting and scheduling urban road construction projects.* Transportation Research Part E: Logistics and Transportation Review, 2019. 130: p. 161-183.

[4] Hojjati-Emami, K., B. Dhillon, and K. Jenab, *Reliability prediction for the vehicles equipped with advanced driver assistance systems (ADAS) and passive safety systems (PSS).* International Journal of Industrial Engineering Computations, 2012. 3(5): p. 731-742.

[5] Du, Z.-P. and A. Nicholson, *Degradable transportation systems: sensitivity and reliability analysis.* Transportation Research Part B: Methodological, 1997. 31(3): p. 225-237.

[6] Naresky, J.J., *Reliability definitions.* IEEE Transactions on Reliability, 1970. 19(4): p. 198-200.

[7] Sumalee, A., D.P. Watling, and S. Nakayama, *Reliable network design problem: case with uncertain demand and total travel time reliability.* Transportation Research Record, 2006. 1964(1): p. 81-90.

[8] Chen, A., et al., *Transport network design problem under uncertainty: a review and new developments.* Transport Reviews, 2011. 31(6): p. 743-768.

[9] Wardrop, J.G. and J. Whitehead, *Correspondence. some theoretical aspects of road traffic research.* Proceedings of the Institution of Civil Engineers, 1952. 1(5): p. 767-768.

[10] Herman, R. and T. Lam, *Trip time characteristics of journeys to and from work.* Transportation and traffic theory, 1974. 6: p. 57-86.

[11] Richardson, A. and M. Taylor, *Travel time variability on commuter journeys.* High Speed Ground Transportation Journal, 1978. 12(1).

[12] Polus, A., *A study of travel time and reliability on arterial routes.* Transportation, 1979. 8(2): p. 141-151.

[13] Al-Deek, H. and E.B. Emam, *New methodology for estimating reliability in transportation networks with degraded link capacities.* Journal of intelligent transportation systems, 2006. 10(3): p. 117-129.

[14] Van Lint, J., H.J. Van Zuylen, and H. Tu, *Travel time unreliability on freeways: Why measures based on variance tell only half the story.* Transportation Research Part A: Policy and Practice, 2008. 42(1): p. 258-277.

[15] Pu, W., *Analytic relationships between travel time reliability measures.* Transportation Research Record: Journal of the Transportation Research Board, 2011(2254): p. 122-130.

[16] Institute, T.T., *Providing a Highway System with Reliable Travel Times.* F-SHRP Web Document 3. Transportation Research Board of the National Academies, Washington, D. C., 2003.

[17] Clark, S. and D. Watling, *Modelling network travel time reliability under stochastic demand.* Transportation Research Part B: Methodological, 2005. 39(2): p. 119-140.

[18] Dui, H., et al., *Model and simulation analysis for the reliability of the transportation network.* Journal of Simulation, 2020: p. 1-10.

[19] Liu, J., et al., *Connectivity Reliability on an Urban Rail Transit Network from the Perspective of Passenger Travel.* Urban Rail Transit, 2020. 6(1): p. 1-14.

[20] Wakabayashi, H. and Y. Iida, *Improvement of road network reliability with traffic management.* IFAC Proceedings Volumes, 1994. 27(12): p. 603-608.

[21] Lee, S., B. Moon, and Y. Asakura, *Reliability analysis and calculation on large scale transport networks.* Reliability of transport networks. Research Studies Press Ltd, 2000.

[22] Chen, A., P. Kasikitwiwat, and C. Yang, *Alternate capacity reliability measures for transportation networks.* Journal of Advanced Transportation, 2013. 47(1): p. 79-104.

[23] Chiou, J.-M., H.-T. Liou, and W.-H. Chen, *Modeling Time-Varying Variability and Reliability of Freeway Travel Time Using Functional Principal Component Analysis.* IEEE Transactions on Intelligent Transportation Systems, 2019.

[24] Zhang, Z., et al., *Analyzing travel time reliability and its influential factors of emergency vehicles with generalized extreme value theory.* Journal of Intelligent Transportation Systems, 2019. 23(1): p. 1-11.

[25] Lu, C., et al., *Incorporating the standstill distance and time headway distributions into freeway car-following models and an application to estimating freeway travel time reliability.* Journal of Intelligent Transportation Systems, 2019: p. 1-20.

[26] Knoop, V.L., et al., *Link-level vulnerability indicators for real-world networks.* Transportation Research Part A: Policy and Practice, 2012. 46(5): p. 843-854.

[27] El-Rashidy, R.A. and S.M. Grant-Muller, *An assessment method for highway network vulnerability.* Journal of Transport Geography, 2014. 34: p. 34-43.

[28] Wang, D.Z., et al., *Identification of critical combination of vulnerable links in transportation networks–a global optimisation approach.* Transportmetrica A: Transport Science, 2016. 12(4): p. 346-365.

[29] Bagloee, S.A., et al., *Identifying critical disruption scenarios and a global robustness index tailored to real life road networks.* Transportation Research Part E: Logistics and Transportation Review, 2017. 98: p. 60-81.

[30] Vodák, R., et al., *A deterministic approach for rapid identification of the critical links in networks.* PloS one, 2019. 14(7).

[31] Gecchele, G., R. Ceccato, and M. Gastaldi, *Road Network Vulnerability Analysis: Case Study Considering Travel Demand and Accessibility Changes.* Journal of Transportation Engineering, Part A: Systems, 2019. 145(7): p. 05019004.

[32] Cantillo, V., L.F. Macea, and M. Jaller, *Assessing vulnerability of transportation networks for disaster response operations.* Networks and Spatial Economics, 2019. 19(1): p. 243-273.

[33] Tian, Z., et al., *Key links identification for urban road traffic network based on temporal-spatial distribution of traffic congestion.* Modern Physics Letters B, 2019. 33(25): p. 1950307.

[34] Guo, S., et al., *Identifying the most influential roads based on traffic correlation networks.* EPJ Data Science, 2019. 8(1): p. 1-17.

[35] Poorzahedy, H. and S.N.S. Bushehri, *Network performance improvement under stochastic events with long-term effects.* Transportation, 2005. 32(1): p. 65-85.

[36] Chen, H. and H.A. Rakha, *Real-time travel time prediction using particle filtering with a non-explicit state-transition model.* Transportation Research Part C: Emerging Technologies, 2014. 43: p. 112-126.

[37] Iida, Y. and H. Wakabayashi. *An approximation method of terminal reliability of road network using partial minimal path and cut sets*. in *Transport policy, management & technology towards 2001: selected proceedings of the fifth world conference on transport research*. 1989.

[38] Valiant, L.G., *The complexity of enumeration and reliability problems.* SIAM Journal on Computing, 1979. 8(3): p. 410-421.

[39] Shier, D.R., *Network reliability and algebraic structures*. 1991: Clarendon Press.

[40] Konak, A. and A. Smith. *A general upperbound for all-terminal network reliability and its uses*. in *Proceedings of the Industrial Engineering Research Conference*. 1998.

[41] Sharafat, A.R. and O.R. Ma'rouzi, *All-terminal network reliability using recursive truncation algorithm.* IEEE Transactions on Reliability, 2009. 58(2): p. 338-347.

[42] Satyanarayana, A., *A unified formula for analysis of some network reliability problems.* IEEE Transactions on Reliability, 1982. 31(1): p. 23-32.

[43] Fishman, G.S., *A Monte Carlo sampling plan for estimating network reliability.* Operations Research, 1986. 34(4): p. 581-594.

[44] Karp, R.M. and M. Luby. *Monte-Carlo algorithms for enumeration and reliability problems*. in *Foundations of Computer Science, 1983., 24th Annual Symposium on*. 1983. IEEE.

[45] Everitt, B. and A. Skrondal, *The Cambridge dictionary of statistics*. Vol. 106. 2002: Cambridge University Press Cambridge.

[46] Farahani, R.Z., et al., *A review of urban transportation network design problems.* European Journal of Operational Research, 2013. 229(2): p. 281-302.

[47] Bryden, K.M., et al., *Optimization of heat transfer utilizing graph based evolutionary algorithms.* International Journal of Heat and Fluid Flow, 2003. 24(2): p. 267-277.

[48] Beheshti, A. and S. Hejazi, *A Quantum evolutionary algorithm for the vehicle routing problem with delivery time cost.* International Journal of Industrial Engineering and Production Research, 2014. 25(4): p. 287-295.

[49] Mani, N. and A. Mani, *Solving Combinatorial Optimization problems with Quantum inspired Evolutionary Algorithm Tuned using a Novel Heuristic Method.* arXiv preprint arXiv:1612.08109, 2016.

[50] Narayanan, A. and M. Moore. *Quantum-inspired genetic algorithms*. in *Evolutionary Computation, 1996., Proceedings of IEEE International Conference on*. 1996. IEEE.

[51] Han, K.-H. and J.-H. Kim. *Genetic quantum algorithm and its application to combinatorial optimization problem*. in *Evolutionary Computation, 2000. Proceedings of the 2000 Congress on*. 2000. IEEE.

[52] Han, K.-H. and J.-H. Kim, *Quantum-inspired evolutionary algorithm for a class of combinatorial optimization.* IEEE transactions on evolutionary computation, 2002. 6(6): p. 580-593.

[53] Zhang, G., *Quantum-inspired evolutionary algorithms: a survey and empirical study*. Journal of Heuristics, 2011. 17(3): p. 303-351.

[54] Kourank Beheshti, A. and S.R. Hejazi, *A Quantum Evolutionary Algorithm for the Vehicle Routing Problem with Single-sided Time Window Setting.* International Journal of Industrial Engineering & Production Research, 2014. 25(4): p. 287-295.