Finding the Nearest Facility Considering Travel and Waiting Time in a Transport Network

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Abstract

One of user's queries from navigation service is to find the nearest facility in terms of time. The facility that is being questioned by the user as a destination may have a queuing service system (e.g. bank), which means that the cost function of the shortest path includes the waiting time at the destination as well as the travel time. This research conducts in the zone 1 of Mashhad with Bank at destination. In this research, we first calibrate the volume-travel time function to predict travel time by using history volume data of SCATS. The results of the analysis show the Moving-Average model with a period of 4 weeks is more precise to predict volumes and consequently travel time. Then we use Simulation-based method to predict waiting times in Bank. A* algorithm with different scenarios is applied to solve the shortest path problem. This algorithm is compared with the Dijkstra's algorithm in different networks. Results show by increasing the nodes of network, the required time to solve the A* algorithm is significantly lower than the Dijkstra's algorithm. In general, this study indicates the A* algorithm and the suggested heuristic function reduce run time for solving the shortest path problems.

Keywords: Travel time prediction, volume-travel time function, waiting time, simulation, shortest path

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1. Introduction

A large part of the citizen's time is wasted in traffic jams every day, which imposes a heavy burden of costs (e.g. fuel consumption, etc.) on citizens. One of the main problems of people's minds is finding a solution to reduce the time of their inland city trips. The role of navigation systems is becoming more and more important due to the capabilities that they provide for people in order to get better solutions. In such a situation, being aware of network status is essential for choosing the best route. One of the goals of the Intelligent Transportation System (ITS) and the travel information system is to provide up-to-date information from the transport network to travelers for making better decisions. The travel time of the transport network arcs is the most important parameter in selecting the route. Continuous changes of traffic flow during the time lead to the change of the travel times of transportation network. These changes show the importance of time in spatial analysis. Routing under such conditions is known as dynamic routing [Cooke and Halsey 1966], so there are two common types of queries for ITS by navigation service. The first query deals with finding an optimal route from the current location to the desired destination. The other query allows users to locate the nearest facility of a certain category use, such as the nearest hotel, hospital or gas station, without knowing the destination in advance [Wu 2006]. In the second query, a facility that is being questioned by the user as a destination may have a queuing service system (e.g. Bank). This paper tries to find the shortest path regarding travel and waiting time at the destination as well as less runtime through the A* algorithm. That is, it would find the route and destination which has the minimum time from the beginning of the journey until the departure of the destination. The remainder of our research is organized as follows. In Section 2 the literature review is presented. Section 3 draws attention to the problem statement. Solving method is discussed in Section 4 and the computational results for the model is presented in Section 5. Section 6 includes discussion and conclusion of the study.

2. Literature Review

The problem of finding the shortest path between the two points has been one of the most practical issues in transport spatial analysis as well as geographical position systems. Various criteria such as distance, travel time, path comfort, path beauty, etc. are considered for analyzing the shortest path in geographical position systems [Saberian J. 2009]. The Dijkstra’s algorithm was proposed in 1959 as the shortest path finding algorithm, which has been used as a basic algorithm in a non-negative-weight graph for many algorithms to date [Ahmadi, Ebadi, and Valadan 2008]. Routing algorithms are divided into two categories according to the number of origin and destination points, matrix algorithms and tree algorithms. Matrix algorithms find the shortest distance between all pairs of nodes in the grid with repetitive operations, but the tree structure algorithm finds the shortest path from the certain node to the other nodes. Tree algorithms are such as Dijkstra's algorithm [Ciesielski et al, 2018], Bellman-Ford (Bellman 1958) and A* algorithm [Chandak et al, 2016], and matrix algorithms include Floyd-Marshall [Gosper 1998] and Johnson algorithm [Cook 1999]. The time complexity of tree algorithms is less than matrix algorithms, which often not used for routing in spatial information systems [Cherkassky, Goldberg, and Radzik 1996]. The shortest path problems can also be divided into two subcategories: static and dynamic [Schmitt and Jula 2006]. The dynamic shortest path problem is generalized from that of static for which the network property (e.g. cost of arcs) changes, over the time. Generally, the shortest path algorithms in dynamic state can be classified into two classes. First Time-dependent shortest path problem, of which, network characteristics change with time in a predictable fashion. In this type, each link has a predictable function of travel time with respect to time; Second, recalculation of optimal path due to consecutive, instantaneous and unpredictable changes in network data [Dean 2004]. Ardakani et al. [Ardakani and Tavana 2015] studied time-dependent shortest path problem using a decremental approach to reduce the network size and speed-up the optimization process. Their approach indicated a significant decrease in CPU times up to 45%, but cost function was higher than optimal value.

The travel time prediction refers to the calculation of travel time before the user traverse the desired path. So far, several methods have been used to determine the travel time of an arc. Taylor and Bonsall [Taylor, Bonsall, and Young 2000] classified methods into two broad categories for measuring the travel time in a transit network. The first category, also known as the site base method, determines the travel time based on the passing of cars from a specific point. The second category, also known as the floating-car method, measures the travel time along the arc of a network based on traffic flow. Loop detectors, Sydney Coordinated Adaptive Traffic System (SCATS), and cameras are fixed equipment used for the site base methods to measure the travel time along urban corridors. Thus, the equipment placed on the path is capable of counting and registering the number of vehicles passing along a section of the path [Spencer, Labell, and May 1989].

Many approaches have been proposed to predict the travel time in the last decade. Most recent studies have been carried out to predict the travel time along the highway using various methods, such as time series models [Ahmed and Cook 1979; Al-Deek, D'Angelo, and Wang 1998; Van Arem et al. 1997], neural networks [Rilett and Park 2001; Zhu, Cao, and Zhu 2014], parametric and nonparametric regression models [Kwon, Coifman, and Bickel 2000; Rice and Van Zwet 2004; Zhang and Rice 2003], support vector machines [Wu, Ho, and Lee 2004], probabilistic [Aron, Bhouri, and Guessous 2014; Guessous et al. 2014] and simulation models [Kamga, Mouskos, and Paaswell 2011]. [Shiripour, Mahdavi-Amiri, and Mahdavi 2017] and [Shiripour, Mahdavi-Amiri, and Mahdavi 2016] Studied the impact of distribution of the population on the travel times of arcs simultaneously, showing the selected route by commuters affect other's travel time.

Various parameters, such as speed, traffic volume, density, etc. are usually utilized to estimate the travel time in the urban networks. Selecting the appropriate parameters is essential to estimate the travel time because the travel time of the urban networks is affected by the traffic conditions and delays at the intersections. The electronic devices, such as mobiles, Global Positioning System (GPS) in automobiles, Bluetooth or Wi-Fi, can be used as a way to measure the travel times and travel speeds. This method is not effective at the time of stopping vehicles. Thus, this method tend to be used lesser in urban networks [Contain 2008]. The data of average speed and instantaneous speed are available through the loop detector and local equipment, such as cameras and floating cars. However, methods of estimating travel time based on traffic volume are more accurate than those of speed-based travel time estimation [Van Lint 2006]. Volume-travel time functions have been developed to estimate the travel time based on the traffic volume data, which show the relationship between the travel time in the streets and traffic volume. Forasmuch as some factors, such as the physical characteristics, traffic volume and composition, drivers' behaviors, and the specific regional conditions, affect the travel time [Comprehensive Transportation Studies in Mashhad, volume-travel time functions 1996]. These factors are partially investigated when measuring the parameters of Volume-travel time functions [Updating Comprehensive Transportation

Studies in Mashhad,make travel time-volume function models for the main roads 2010]. Some researchers studied location-Routing problems which the objective of such problems is finding the best place among the candidate places to locate a specific facility in a region in order to minimize the total cost, including the facility set up cost as well as the transportation cost. For instance, [Shiripour and Mahdavi-Amiri 2018] applied two metaheuristic approaches for such problem which their aim was allocating the type and number of vehicles to the injured people in the disaster regions so that the total relief time is minimized.

Most of the studies have done predicting travel time on highways and found shortest path without a facility at destination. In this study, we investigated to find the nearest facility regarding travel time in urban area and waiting time in facility (the overall of travel time and waiting time). Another innovation is employing new heuristic function to find shortest path problem in less runtime, which have not been investigated in other studies.

Shortest path problem refers to finding the shortest path before the start of the travel, hence, it is necessary to predict the travel time of the network arcs based on their conditions and then solve the shortest path problem by means of the routing algorithms with as little time as possible. Therefore, as to achieve the objectives of this study the following steps are taken:

(1) Prediction of travel time in urban area and waiting time at queuing service system (e.g. bank) in dynamic conditions.

(2) Applying the A* algorithm to speed-up the optimization process in dynamic shortest path problems.

3. Problem Statement

In the shortest path problem, the goal is to determine the shortest path between the origin and destination points on a graph. A dynamic weighted directed graph can be represented as G (N, A), where N is a set of nodes, A is a set of arcs, that the weight of the arcs vary over time. The current section provides the problem of choosing the optimal route-destination with consideration of the waiting time at the destination. Urban transport network can be considered as a weighted directed graph whose intersections define nodes and streets constitute the arcs. In our problem, the arcs of the network are divided into two types. The first type of arcs is related to the urban transport network, which varies based on traffic changes. The second type of arcs is related to the waiting time in the system of the banks, which varies based on the arrival and departure rate of their customers. Figure 1 shows an example of the problem graph with two banks (B1 and B2). The transport network graph is displayed with nodes and solid directed lines (nodes 1 to 7); the weight of each arc (wij) is its travel time. The unidirectional arcs (dashed lines) are added to transport network to show waiting time in the bank, which means the weight of these arcs is related to waiting time in bank. Finding the shortest path from node 1 to node 8 (hypothetical node) provides the optimal route and bank in terms of the time criterion. In other words, this route shows the least time from the beginning of the movement to the departure of the bank.

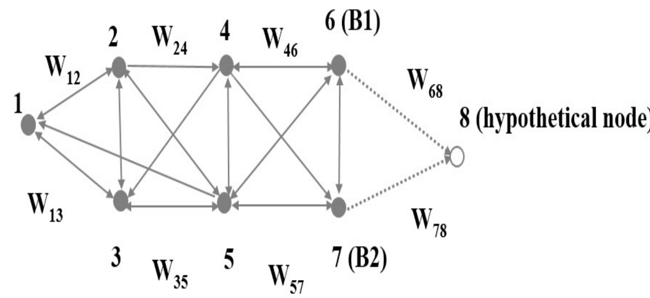

Figure 1. Graph with two banks

4. Problem-Solving Method

For finding shortest path in network we need to estimate the weight of arcs, at first. As it was mentioned in the previous section, the arcs in our problem fall into two categories which are known as travel time arcs in transport network and waiting time arcs in destination (e.g. bank). Thus we apply two different methods for estimating of such two arcs, the former arcs use time series and the latter is based on simulation. Finally, we use a heuristic function in A* algorithm to find the nearest bank regarding minimum overall travel time and waiting time simultaneously. The figure 2 shows the flowchart of the research method in this study.

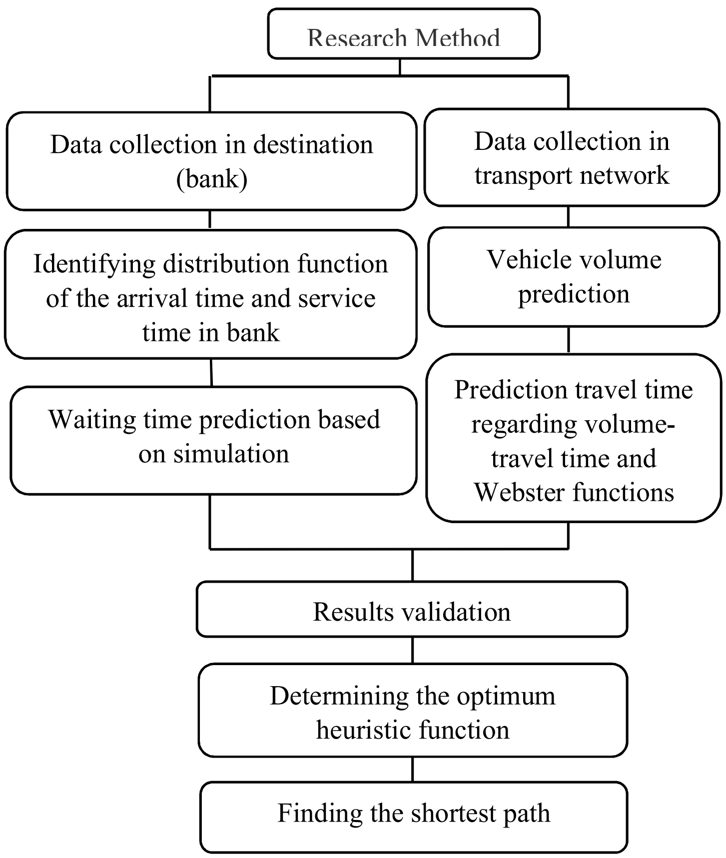

Figure 2. The flowchart of the research method

4.1. Case Study and Data Collection

Mashhad is the second most populous city in Iran. Its population was 3,218,208 at the 2015 census. It covers an area of 352.3 km^2. Considering the population of this city, a lot of people spend their time in urban traffic. This study aims to predict the travel time and waiting time in banks in the zone 1 of Mashhad, consisting of 22 intersections and 48 streets. Figure 3 shows the zone under study, which has three types of streets, including collector, primary arterial and secondary arterial streets. These streets are selected because firstly, in urban area the traffic often take place in them and secondly, the loop detectors used for data gathering have installed in these roads. In addition, there are 4 banks in this figure that is showed with letter (B).

In order to develop the volume-travel time functions and actually obtain constant parameters and coefficients in proportion to the travel behavior in the city, it is necessary to collect a series of data on daily travels of individuals. The data collect as a journey time survey. There are several methods, such as registering a license plate and sample vehicle, to collect the data. The Mashhad Traffic and Transportation Organization collect the data on the number of passing vehicles in collector and arterial streets, highways, etc. using the SCATS. Instead of the registration of license plates, the recorded data of this system can be used. Additionally, field survey can be used for verification. The data on the volume of transit vehicles were obtained from the Mashhad Traffic and Transportation Organization for 15-minute periods from 2014/10/26 to 2014/12/24 in typical traffic conditions.

Figure 3. Zone under study (zone 1 of Mashhad)

4.2 Travel Time Estimation

One of the methods used to estimate the travel time is the volume-travel time function. For the volume-travel time function, different mathematical models have been proposed. The most famous model is the Bureau of Public Roads (BPR), equation (1) presents that. In the studies conducted in Mashhad, the data required for developing this function have been collected and the parameters of the function have been estimated [Updating Comprehensive Transportation Studies in Mashhad,make travel time-volume function models for the main roads 2010].

$$T=t_0\,[1+a\,(V/Q)^{\,b}] \quad (1)$$

T: Average travel time (minute), t0: Average free travel time (minute), V: Traffic volume (passenger car per meter per hour), Q: Practical capacity (passenger car per meter per hour), a, b: model parameters.

Since each arc has a signalized intersection, it is necessary to consider the amount of traffic light delay for calculating the total travel time. In this study, Webster's model is used to calculate the delay time of the traffic light because the timing of the intersections in the zone under study is compatible with this model; the mathematical expression of this model is based on the equation (2) (Akcelik 1988; Urbanik et al. 2015).

$$d = \frac{(c-g)^2}{2c(1-\frac{v_i}{s})} + \frac{R^2}{2v_i(1-R)} - 0.65\left(\frac{c}{{v_i}^2}\right)^{1/3} R^{2+5\left(\frac{c}{g}\right)} \quad (2)$$

d: Average delay time for crossing the intersection (sec), Vi: Traffic volume of the entrance to the intersection (passenger car per meter per hour), s: Saturation flow rate (passenger car per meter per hour), g: Green time (sec), c: Cycle length (sec).

The value of R in the Webster function is defined as the equation (3):

$$R = (v_i/s)\,/\,(g/c) \quad (3)$$

The linear combination of the BPR and Webster functions to estimate the travel time present in the equation (4).

$$T = \alpha B + \beta D \quad (4)$$

Where B is the amount of travel time of the arc, D is the delay time of the traffic signal, α and β are the linearization coefficients. Using the least squares error regression model, α and β coefficients are 0.95 and 1.13 (R^2= 0.95) for the primary arterial streets, respectively, and this coefficients are 0.90 and 1.08 (R^2= 0.93) respectively, for Secondary arterial and collector streets.

4.2.1 Vehicle Volume Prediction to Estimate the Travel Time

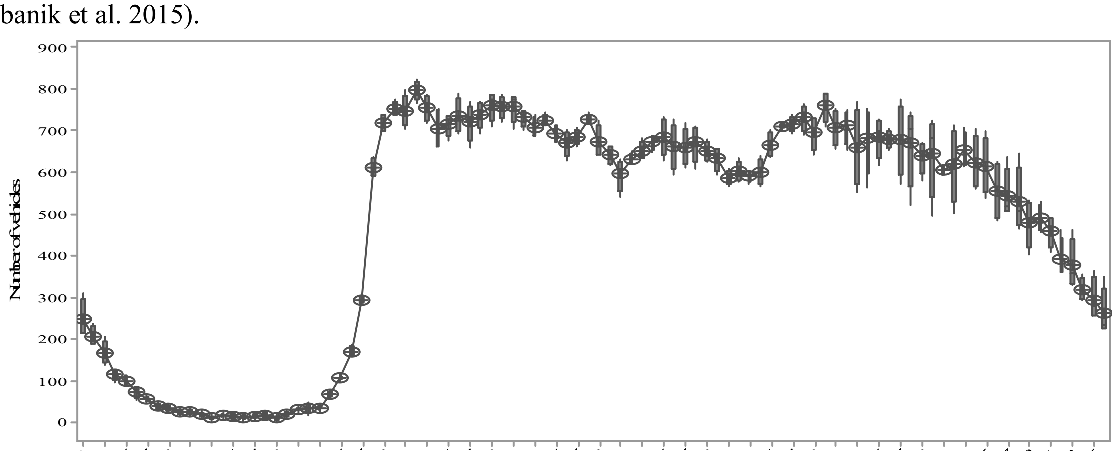

Figure 4. Volume of vehicles on Sanabad Street in 96 intervals

The available data for estimating travel time are the volume of vehicles. For prediction based on history information, several time series methods can be used, such as simple moving average, weighted moving average, exponential smoothing, trend determining method, etc. [Box et al. 2015]. The appropriate pattern for the time series data must first be created to select the appropriate method for prediction. In practice, traffic patterns can be grouped annually, monthly, weekly, daily, and hourly. Anil Kumar et al. analyzed the pattern of GPS-based bus travel time data. Their results show that the travel time pattern is different for different days of the week [Kumar, Vanjakshi, and Subramanian 2013]. To avoid verbosity, we present analysis on Monday and on Sanabad (Palestine-Rahnamaee) street. Figure 4 shows the box-plot chart for the volume of vehicles on Sanabad (Palestine-Rahnamaee) street in a 24-hour period in sequence weeks (4 weeks) from a given day (Monday). At this figure the volume of vehicles has a very stable behavior on the given day of the week. In order to approve this hypothesis, use the One-way analysis of variance with blocking (ANOVA) to examine the vehicle volume behavior on different days.

Table 1 shows the results of analysis of variance with blocking, 4 factors (weeks) and 96 blocks (the number of 15-minute intervals per day) on Sanabad street on Monday. At the 5% significance level, factor source does not reject. In other words, there is no difference between the mean-values for the number of vehicles at the same intervals from the given day of the consecutive weeks. The p-value of the block source, shows the vehicle volume at different intervals from a given day is not equal. In fact, it confirms the assumption of the dynamics or variation of the vehicle volume in different periods of a day. Therefore, the vehicle volume data from a certain day of the previous weeks are used to predict the vehicle volume in a 15-minute period of the given day. For example, the history vehicle volume data from 9 to 9:15 on Mondays are used to predict the vehicle volume from 9 to 9:15 on next Monday. Thus, the analysis was separately done for different days of the week and different intervals. Given that the vehicle volume data in the same period for the same day have the same behavior for consecutive weeks, the simple moving average method is used to predict the volume of vehicles. In order to select the appropriate period in the moving average, the mean prediction error of the different periods is calculated, and a period with a lower mean error is selected. In this study, the period selected is with a size of 4 and a mean prediction error of 0.1.

Table 1. One-way Analysis of variance with blocking on Sanabad Street on Monday

Source	DF	MS	F-value	P-value
Block (Interval)	**95**	**307900**	**290.12**	**0.000**
Factor (Week)	**3**	**554**	**0.52**	**0.667**
Error	**285**	**1061**	**-**	**-**
Total	**383**	**-**	**-**	**-**

In order to validate the method of estimating the travel time, the results obtained from Section

4.2 are compared with actual values. The actual travel time can be measured by different methods as the above mentioned and in this paper it was measured using a floating car along the arc and recording the arrival and departure times of the arc via a stopwatch. The difference between the arrival and departure times of the arc represents the travel time of the arc. For increasing the accuracy of the measurement, the travel time was measured five times for each arc, and the mean value of five times considered as the actual travel time of the arc.

The paired T-test was used at the 95% confidence interval to test the assumption of the equality of the estimated and actual values for each street classification. The null hypothesis in this test indicates no significant difference between the estimated and actual values. The results of this test are presented in Table 2. The upper and lower bounds in this table show the acceptance area for the null hypothesis at the 95% confidence interval. Given that the p-value is greater than 0.05, the null hypothesis cannot be rejected. In fact, it can be said that the results of the estimation are acceptable Calculation of the waiting time in the queue for real applications is not efficient using analytical methods because of the complexity of the models and the consideration of many assumptions [Banks, Carson, and Nelson 1996]. Therefore, in this study, the method of investigating the system through simulation is presented to predict the waiting time in the bank.

Table 2. Paired T-test for estimated and actual values

Type of street	95% Confidence Interval		P-value
	Lower Bound	Upper Bound	
Primary arterial	-1.7	44.6	0.068
Secondary arterial	-7.2	54.3	0.127
Collector	-1.62	18.27	0.097

4.3 Prediction of Waiting Time in Banks

Waiting in the queue is a common phenomenon in daily life, which seems a waste of time for many people. Therefore, awareness of the queue status before attending there, is one of the most pressing challenges for the people.

4.3.1 Data Collection

The banks activity starts at 7:30 am and ends at 14:00. The travel time prediction for each arc calculated at 15-minute intervals throughout the day, so the simulation of the bank is done at 15-minute intervals. In order to simulate, the data of arrival and service times of customers collected using the field survey for various days in November 2014.

The purpose of the simulation is to obtain the average waiting time of the person in the system based on the arrival time in the bank. For simulation, the components of the system must first be identified correctly. Table 3 presents the components of the problem for the bank system. Table 4 presents the assumptions for the simulation model based on the current conditions of the banks under study. There are two servers and one queue for our bank systems.

4.3.2 Bank Simulation

To simulate each interval, determining the distribution function of the arrival time and service time is necessary. We used The Easy Fit Professional v5.50 software to determine the distribution function of the arrival time and service time based on the collected data. This software has the ability to match data with more than 55 distributions, using the best matching tests, including Kolmogorov-Smirnov, Anderson-Darling, and Chi-Squared. The most powerful test for continuous distribution data is the Kolmogorov-Smirnov test for small to medium sized samples [Wall 1996].

The null hypothesis (the data follow the specified distribution function) is rejected if the p-value < 0.05. For example, Table 5 shows the distribution function of the arrival time and service time for a particular bank (B1) on Monday.

Table 3. Components of bank system

population Size	Queue	Service
Infinite	The queue capacity according to the bank's space is fifty people, First In First Out	Enter to the first empty server

Table 4. Assumptions for the simulation model

System	Entity	Attribute	Activity	Event	Status
Bank	Customers	Arrival time, start service	Banking operation	Arrival and Departure	waiting time in the system

Table 5. Distribution function of the arrival time and service time on bank (B1)

Interval	Arrival time (second)	1st Server	2nd Server
[10:00,10:15)	Exponential (μ=210)	Exponential (μ=269)	Exponential (μ=157)
[10:15,10:30)	Exponential (μ=186)	Exponential (μ=253)	Exponential (μ=145)
[10:30,10:45)	Uniform [472,624]	Normal (258,194)	Exponential (μ=142)
[10:45,11:00)	Exponential (μ=172)	Normal (225,133)	Exponential (μ=163)
[11:00,11:15)	Uniform [449,523]	Exponential (μ=232)	Uniform [265,459]
[11:15,11:30)	Normal (350,195)	Exponential (μ=362)	Normal (364,169)
[11:30,11:45)	Uniform [279,324]	Exponential (μ=290)	Exponential (μ=178)
[11:45,12:00)	Exponential (μ=372)	Normal (241,159)	Normal (741,389)
[12:00,12:15)	Normal (446,283)	Normal (157,240)	Normal (463,249)
[12:15,12:30)	Uniform [174,249]	Uniform [47,224]	Normal (252,173)

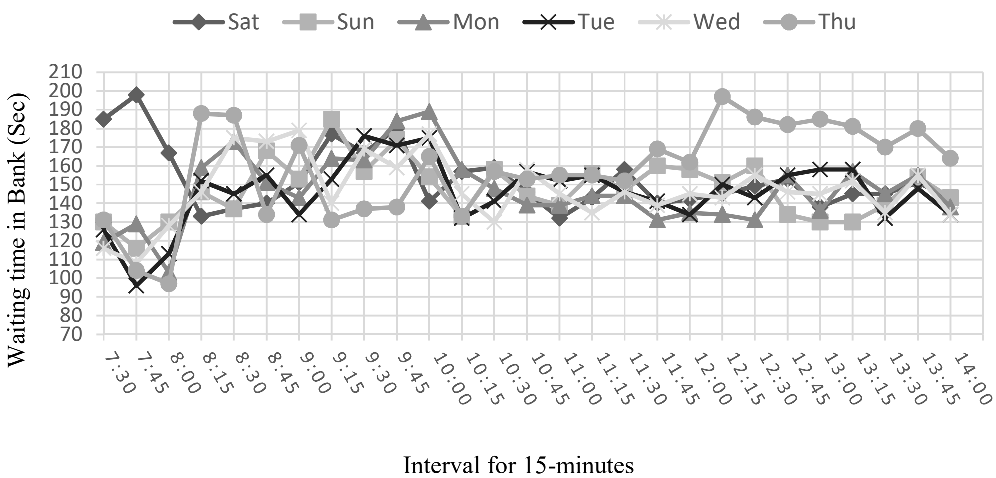

Figure 5. Simulation results for bank (B1)

After determining the distribution function of the arrival time and service time at each 15-minute interval, Enterprise Dynamics software was used for simulation. As shown in Figure 5, the simulation results for each bank is calculated for the weekdays and intervals. For example, this figure is related to B1. The waiting time on Saturday morning and Thursday afternoon are more than other times because before and after these times are the weekends.

Table 6. Results of T-test for several intervals on Monday

Interval	95% Confidence Interval		P-value
	Lower Bound	Upper Bound	
[7:30, 7:45]	-16.51	7.51	0.437
[7:45, 8:00]	-19.19	8.77	0.435
[8:00, 8:15]	-18.73	10.90	0.572
[8:15, 8:30]	-19.93	11.08	0.539
[8:30, 8:45]	-10.64	16.04	0.671
[8:45, 9:00]	-24.8	24.07	0.996

To validate the simulation results, the T-test is used for each 15-minute interval at the 95% confidence interval. For instance, the results of the analysis for several intervals on Monday are presented in Table 6. It can be observed that the results of the simulation are acceptable because the p-value is greater than 0.05.

4.4. A* algorithm

Labelling algorithms are the most famous and most efficient algorithms to solve the shortest path problem. These algorithms use a label for each node that is related to the length of the shortest path to that node. The algorithm continues the update of labels until the shortest path is found. Dijkstra's and A* algorithms are labelling algorithms. Dijkstra's algorithm is one of the methods for the informed search that ensures the optimal path. However, Dijkstra's algorithm is not widely used because of its dependence on the high computational time (Wu 2006). Therefore, the informed search methods have been developed according to the informed searches: the A* algorithm is widely considered as an effective method (Wu 2006). This algorithm tries to minimize the total cost paid from the source to the current node and the remaining cost from the current node to the target. The cost of each node in the A* algorithm calculates using the equation (5).

$$f(n) = g(n) + h(n) \quad (5)$$

g(n) is the cost of the path from the start node to n, and h(n) is a heuristic that estimates the cost of the cheapest path from n to the goal. In the A* algorithm, the next node for expansion is the node that has the lowest value of f(n) among other non-expanded nodes. The A* algorithm avoids expanding non-optimal directions and only searches directions that are more effective in achieving the goal, resulting in reduced computation time. Therefore, the A* algorithm is faster than the Dijkstra's algorithm to find the shortest path between a pair of nodes [Wu 2006]. The estimate of the remaining cost to the target (h(n)) is called a heuristic. The design of the heuristic is very important in the A* algorithm. The optimality of the A* method is influenced by the design of the heuristic. The A* method is able to produce an optimal value if the heuristic is consistent. Equation (6) shows non-descending of h(n) in A* algorithm, which means the next nodes of the graph which are not selected in shortest path will have the less amount towards the traversed nodes.

$$h(n) \ll c(n, a, n') + h(n') \quad (6)$$

Where $c(n, a, n')$ denotes the cost of arc (n, n'). The A* method is efficient for any heuristic function. That is, no other optimal algorithm ensures that the number of expanded nodes is fewer than the A* algorithm [Russell and Norvig 2002].
We present the equation (7) for calculating f(n) in our problem.

$$f(n) = g(n) + h(n) + q(n) \quad (7)$$

Equation (7) illustrates the algorithm finds the nearest bank regarding waiting time, Indeed it is the A* algorithm for finding shortest path that the waiting time in bank, q(n), is added to that in terms of the type of our problem.
The values obtained in the estimation section of the travel time are used for the actual values of arcs (g(n)), the values obtained from the simulation are used for q(n). In order to determine the heuristic function, the first the travel speed is calculated for each arc at different time periods based on the values of the arc travel time and the delay time at the intersection and then the values for h(n), determine based on the speed-time equation. For the speed parameter in the speed-time equation, maximum speed considers based on arcs that have not been selecting for optimal path. For the distance value (length), three scenarios present as follows:

A) Euclidean distance: In this scenario, the Euclidean distance uses to determine the heuristic function between the two nodes.

B) Orthogonal distance: An orthogonal distance between two points uses to determine the heuristic function between the two nodes.

C) Actual minimal distance: In this scenario, the shortest path of real distance (length) calculates based on the Dijkstra's algorithm.

For the dynamics in the routing problem to be considered, the following conditions consider in the algorithm for the node (n) selected for expansion.

If $0<g(n)\leq \Delta\text{-t}$, the algorithm will use the current (first) interval data.

If $\Delta\text{-t} <g(n)\leq 2\Delta\text{-t}$, the algorithm will use the second interval data.

If $i\Delta\text{-t} <g(n)\leq (i+1)\Delta\text{-t}$, the algorithm will use the (i+1) interval data.

Δ denotes the length of the interval (in our problem Δ=15 minutes), t is the start time of the routing, and i is the interval counter.

Let's assume that a journey takes 20 minutes, the journey starts in the tenth minutes of the current interval (first interval). The travel time of the network arcs will change at the next 5 minutes (Δ-t =15-10). Therefore, the algorithm will use the current interval data for the first 5 minutes and the second interval data for the next 15 minutes.

5. Numerical Results

As we said as well as optimal response, the runtime for solving the shortest path is important. Although the selection of Euclidean distance and maximum speed always ensure the optimal value, we examine the other scenarios for finding both factors (optimal response and runtime) simultaneously. Therefore, firstly, the problem ran 208 times (the number of nodes is multiplied by 4 intervals) for each of the three scenarios discussed in Section 4.3, and the obtained results are compared with the results of the Dijkstra's algorithm to determine the percentage of optimization for each scenario. Figure 6 shows the percentage of optimal values for the three scenarios in terms of 208 runs.

After selecting the Euclidean distance for determining the heuristic function, the A* and Dijkstra's algorithms ran 1040 times based on the calculated travel times for the zone under study. The results show that for the 22 nodes, the average runtime of the Dijkstra's and A* algorithms is 147.6 and 73.8 milliseconds, respectively. It is obvious runtime of A* algorithm is less than Dijkstra's one. The difference of runtimes between the two algorithms is negligible because of the low number of nodes and arcs. In order to examine the difference in the runtimes of the two algorithms, the shortest path problem is solved with respect to the California data with the number of different nodes [http://www.dis.uniroma1.it/challenge9/download.shtml.]. Figure 7 illustrates the comparison of the runtime of the Dijkstra's and A* algorithms with the optimal value.

According to the obtained results as shown in Fig. 7, it is clear that the more the number of nodes increases, the more time the Dijkstra's algorithm spends, which is far more than that of the A* algorithm to find the shortest path. For example, when the number of nodes reaches 3000, the runtime of the algorithm is approximately 23 seconds, which is not suitable for web applications by which the user expects his/her request is responded promptly. However, the A* algorithm provides an optimal value for 3000 nodes at a runtime of about 2 seconds.

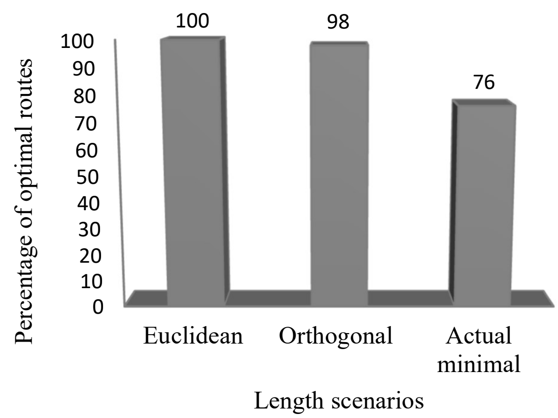

Figure 6. Percentage of optimal routes for different scenarios by 208 runs

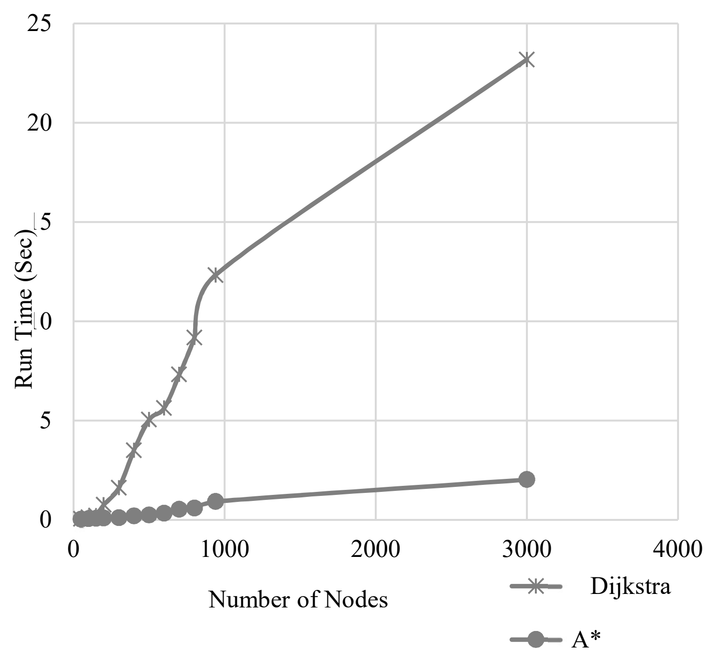

Figure 7. Comparison of the runtimes of the Dijkstra's and A* algorithms

6. Conclusion

The traffic volume in urban networks has usually caused people to search for routes with the least amount of time. Forasmuch as time-based continuous changes in traffic density lead to changes in travel time in the transport network, the use of static metrics for routing will not be sufficiently precise. In addition, in most cases people navigate for the use of a service. In this study, the waiting time at the destination (Bank) was added to the shortest path problem, and features of the dynamic network used for routing. This study is conducted in the zone 1 of Mashhad city. Firstly, the vehicle volume is predicted in each arc per 15-minute interval using the simple moving average method, and then, the arc's travel time and delay at the intersections is calculated using the BPR and Webster functions, respectively. In addition, waiting times are estimated in the bank through the simulation method at the 15-minute intervals. The results shows travel time prediction and waiting time in bank at the 95% confidence interval are acceptable. Finally, the Dijkstra's and A* algorithms with a heuristic function provided solve shortest path problem for different samples, which indicate when the number of nodes increase in the network, the Dijkstra's algorithm loses its efficiency, and the A* algorithm provide the user with the optimal value in less runtime than the Dijkstra's algorithm. In a network with 3000 nodes A* algorithm reduce the runtime up to 91% compared to Dijkstra's algorithm. This paper illustrates finding nearest bank regarding dynamic time at destination and the network at least run time. Further research may also focus on investigating the effects of human factors and uncertain events such as accident on travel time. In addition, different facilities such as petrol station can be considered as a destination.

7. References

-Ahmadi, S., Ebadi, H. and Valadan, Z. (2008) "A new method for path finding of power transmission lines in geospatial information system using raster networks and minimum of mean algorithm", World Applied Sciences Journal, Vol. 3, pp. 269-77.

-Ahmed, M.S. and Cook A.R. (1979) "Analysis of freeway traffic time-series data by using Box-Jenkins techniques", Research Report, Universirt of Oklahoma.

-Akcelik, Rahmi. (1988) "The highway capacity manual delay formula for signalized intersections", ITE Journal, Vol. 58, pp. 23-27.

-Al-Deek, HM, D'Angelo M.P. and Wang MC. (1998) "Travel time prediction with non-linear time series", In Fifth International Conference on Applications of Advanced Technologies in Transportation Engineering.

-Ardakani, M.K. and Tavana, M. (2015) "A decremental approach with the A∗ algorithm for speeding-up the optimization process in dynamic shortest path problems", Measurement, Vol. 60, pp. 299-307.

-Arem, V., Bart, M., Van Der Vlist, J. M., Muste, M. R. and Smulders, S. A. (1997) "Travel time estimation in the GERDIEN project", International Journal of Forecasting, Vol. 13, pp. 73-85.

-Aron, M., Bhouri N. and Guessous Y. (2014) "Estimating travel time distribution for reliability analysis", Research Report, University Pris-Est.

-Banks, J., Carson, J. S. and Nelson, B. L. (1996) "Discrete-event System Simulation", Prentice Hall.

-Bellman, R. (1958) "On a Routing Problem", Quarterly of Applied Mathematics, Vol. 16, pp. 87-90.

-Bhat, U.N. (2015) "An introduction to queueing theory: modeling and analysis in applications", Birkhäuser.

-Box, G. E. P., Jenkins, G. M., Reinsel, G. C. and Ljung, G. M. (2015) "Time series analysis: forecasting and control", John Wiley & Sons.

-Chandak, A., Bodhale, R. and Burad, R. (2016) "Optimal shortest path using HAS, A star and Dijkstra algorithm", Imperial Journal of Interdisciplinary Research, Vol. 2, pp. 978-80.

-Cherkassky, Boris V, Goldberg A.V. and Radzik, T. (1996) "Shortest paths algorithms: Theory and experimental evaluation", Mathematical Programming, Vol. 73, pp. 129-74.

-Contain, T. A. (2008) "Real-time travel time estimates using media access control address matching", ITE Journal, Vol. 78, pp. 20-23.

-Cook, J. D. (1999) "All Pairs shortest path algorithms", Engineering Reports, University of Canterbury.

-Cooke, Kenneth L, and Halsey, E. (1966) 'The shortest route through a network with time-dependent internodal transit times", Journal of Mathematical Analysis and Applications, Vol. 14, pp. 493-98.

-Dean, Brian C. (2004) "Shortest paths in FIFO time-dependent networks: Theory and algorithms", Rapport technique, Massachusetts Institute of Technology.

-Gosper, Jeffrey J. (1998) "Floyd-Warshall All Pairs Shortest Pairs Algorithm", Research Report, Brunei University.

-Guessous, Y., Aron, M., Bhouri, N. and Cohen, S. (2014) "Estimating travel time distribution under different traffic conditions", Transportation Research Procedia, Vol. 3, pp. 339-48.

-Kamga, Camille N., Kyriacos C. M. and Paaswell, R.E. (2011) "A methodology to estimate travel time using dynamic traffic assignment (DTA) under incident conditions", Transportation Research Part C: Emerging Technologies, Vol. 19, pp. 1215-24.

-Kumar, Anil, B., Vanjakshi, L., and Subramanian, S.C. (2013) "Day-wise travel time pattern analysis under heterogeneous traffic conditions", Procedia-Social and Behavioral Sciences, Vol. 104, pp. 746-54.

-Kwon, J., Coifman, B., and Bickel, P. (2000) "Day-to-day travel-time trends and travel-time prediction from loop-detector data", Transportation Research Record: Journal of the Transportation Research Board, Vol. 1717, pp. 120-29.

-Mashhad Traffic and Transportation Organization, (1996) "Comprehensive Transportation Studies in Mashhad, volume-travel time functions", Research Report, Sharif University of Technology.

-Mashhad Traffic and Transportation Organization,(2010)"Updating Comprehensive Transportation Studies in Mashhad,make travel time-volume function models for the main roads", Research Report, Sharif University of Technology.

-Rice, J., and Van Zwet, E. (2004) "A simple and effective method for predicting travel times on freeways", IEEE Transactions on Intelligent Transportation Systems, Vol. 5, pp. 200-07.

-Rilett, Laurence, and Dongjoo P. (2001) "Direct forecasting of freeway corridor travel times using spectral basis neural networks", Transportation Research Record: Journal of the Transportation Research Board, Vol. 1752, pp. 140-47.

-Russell, Stuart J, and Norvig, P. (2002) "Artificial intelligence: a modern approach", Pearson Education Limited.

-Saberian, J., Hamrah M. (2009) "Improving the implementation of routing algorithms in urban networks". In Geomatics Conferences and Exhibitions, K. N. Toosi University of Technology.

-Schmitt, E, and Jula, H. (2006) "Vehicle route guidance systems: Classification and comparison", In Intelligent Transportation Systems Conference, IEEE, pp. 242-47..

-Shiripour, S., and Mahdavi-Amiri, N. (2018) "Optimal distribution of the injured in a multi-type transportation network with damage-dependent travel times: Two metaheuristic approaches", Socio-Economic Planning Sciences, doi.org/10.1016/j.seps.2018.10.011

-Shiripour, S., Mahdavi-Amiri, N., and Mahdavi, I. (2016) "Optimal location-multi-allocation-routing in capacitated transportation networks under population-dependent travel times", International Journal of Computer Integrated Manufacturing, Vol. 29, pp. 652-676.

-Shiripour, S., Mahdavi-Amiri, N., and Mahdavi, I. (2017) "A nonlinear model for location-allocation-routing problem in transportation network with intelligent travel times", International Journal of Operational Research, Vol. 29, pp. 400-431.

-Spencer, M., Labell, L.N., and D May, A. (1989) "Detectors for Freeway Surveillance and Control: An Update", Research Report, University of California, Berkeley.

-Taylor, MAP, Bonsall, P.W., and Young, W. (2000) "Data on travel times. In, Understanding Traffic Systems: Data, Analysis and Presentation". Ashgate Publishing Ltd, pp. 197-206.

-Urbanik, T., Tanaka, A., Lozner, B., Lindstrom, E., Lee, K., Quayle, Sh., Beaird, S., Tsoi, Sh., Ryus, P., and Gettman, D. (2015) "Signal Timing Manual", Research Report, Transportation Research Board.

-Van Lint, JW. (2006) "Reliable real-time framework for short-term freeway travel time prediction", Journal of transportation engineering, Vol. 132, pp. 921-32.

-Wall, JV. (1996) "Practical statistics for astronomers-ii. correlation, data-modelling and sample comparison", Quarterly Journal of the Royal Astronomical Society, Vol. 37, p. 519.

-Wu, Ch.H., Ho, J.M., and Lee, D.T. (2004) "Travel-time prediction with support vector regression", IEEE Transactions on Intelligent Transportation Systems, Vol. 5, pp. 276-81.

-Wu, Q. (2006) "Incremental routing algorithms for dynamic transportation networks", Master of Science, University of Calgary.

-Zhang, X., and Rice, J.A. (2003) "Short-term travel time prediction", Transportation Research Part C: Emerging Technologies, Vol. 11, pp. 187-210.

-Zhu, J.Zh., Cao J.X., and Zhu, Y. (2014) "Traffic volume forecasting based on radial basis function neural network with the consideration of traffic flows at the adjacent intersections", Transportation Research Part C, Emerging Technologies, Vol. 47, pp. 139-54.