

A protocol for optimizing travel time and accessing the shortest route in metropolitan areas using dynamic routing and neural networks algorithms

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Abstract— with the advancement of communication systems, intelligent traffic systems play an important role in optimizing the traffic flow in large and densely populated cities. Today, widespread broadband networks provide real time traffic data sets that intelligently optimize traffic routing. With this in mind, this paper presents a model for calculating street travel time. Each vehicle, upon arrival, receives the optimal route dynamically according to its source and destination. The urban traffic situation is reviewed periodically and using the method of detection and prediction of congestion, streets susceptible to traffic congestion are identified and using the proposed algorithm of vehicle selection, selected vehicles are re-routing using the Dijkstra algorithm and based on shortest route possible. The evaluation shows that the average travel time of the proposed method compared to other research methods, such as EBKSP and FBKSP, was reduced 16% and 20% respectively, and 8% compared to AR method. The results also show that the average number of rerouting in the PDDVRF method decreased by 0.71 for each vehicle compared to 0.8 for the EBKSP and 0.85 for FBKSP method, and an increase of 0.11 was found for the AR method. In the following, the average waiting time for drivers for different traffic conditions is compared. In addition to routing the cars based on the current situation, the traffic lights are dynamically adjusted. The results of the performance evaluation of the proposed method by simulation show the performance of the proposed model in optimizing the traffic flow.

Key word: *Neural network, Dynamic Routing, Travel optimization, urban traffic, intelligent systems*

I. INTRODUCTION

How to manage urban traffic and transport issues is one of the problems of most modern societies. The volume of vehicles is exponentially expanding, which slows the movement of vehicles, causes heavy traffic in the city and causes long stops behind traffic lights. To manage and control the traffic in these big cities, we need a system that effectively addresses the traffic in the city and has the best response to it. Today, various strategies are used to control urban traffic. In addition to the use of signs and traffic lights, the use of offline and online route suggestion to drivers is also a good way to minimize driver travel times and smoothing traffic flow in the city. Although offline suggestion can provide drivers with appropriate routes based on historical data, they do not consider sudden changes in the city. Providing online routing can be achieved by collecting traffic data using city sensors

and transferring these data to a control and decision-making center.

Despite traffic data, traffic control systems can calculate and suggest routes that currently have less traffic, but despite such information, if these systems are not properly managed, these systems may attempt to reduce congestion but the traffic may be transferred from one point to another at the city. The impact of a routing on other routing is one of the main challenges in optimizing the traffic flow. Traffic can be optimized by collecting the route of the cars and taking into account the effect of the routing of a car on the routing of other vehicles.

Figure 1 shows the overall scheme of our smart city. It is assumed that the cars in city are connected to the Internet and send traffic information to the Traffic Control Center, such as the current position obtained from the GPS, its source, destination and route. They also receive the necessary traffic information, such as the city's traffic situation and the proposed route from the control system. Network-connected objects, such as city sensors, are responsible for collecting traffic data such as vehicle speed, number of vehicles in streets, etc. Using the Internet of Things, it is possible that these data are collected from the city and sent to data centers and data analyzes for review, which can be located on Cloud platforms. Another assumption is traffic lights that are connected to the control center via communication networks such as fiber optic, wireless, etc. Traffic lights can make decisions based on the local traffic data collected by the sensors, or the central control system can adjust the traffic light using the general information obtained from the city and the policies. [1][5].

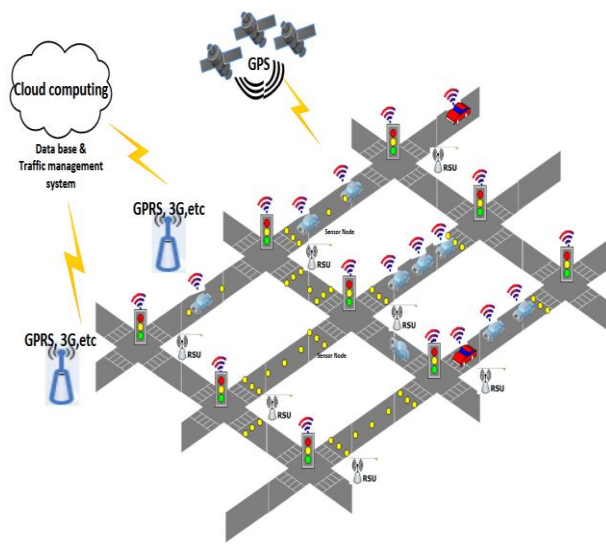


Figure 1. The schematic of the proposed smart city

Also, in this study, using a car travel forecasting model, in which the impact of traffic lights is considered, the time needed for a car to enter a street until it leaves the desired street is calculated. A weighted graph of the city is constructed and the graph weight is the time it takes to travel the street. After identifying the high traffic streets, susceptible cars are selected that by changing their route can reduce the traffic of these streets and the Dijkstra routing algorithm is used to get the shortest possible for cars and using the existing routes, a route with shortest time possible will be sent to the car. It should be noted that in this research it is assumed that the cars accept the suggested route.

In general, there are various methods to reduce the travel time of vehicles, such as the dynamic configuration of traffic lights, dynamic routing, etc., and a proper management and appropriate decision making can be achieved by combining these methods. The traffic lights are dynamically considered in this study. The traffic lights are dynamically activated by the help of sensors, so that traffic lights in the streets can keep the green time up to the maximum defined time, and if there is no car on the street, it will change to another state.

This paper focuses on the distribution of traffic flows between city streets and reducing the average travel time and waiting time for drivers. Also, a travel time prediction model has been used on each street. The use of this prediction model has made the city traffic data much more accurate than previous research. Another objective of this paper is to improve city traffic through data from emerging and developing equipment and technologies. Using actuators and sensors with micro-electromechanical technologies (MEMS) and their wireless communications, broadband networks, cloud computing and integration with IoT, one can obtain sufficient knowledge of the environment and make decisions are more accurate [1-5].

II. BASIC DEFINITIONS

With the city's increasing expansion, the movement of humans and goods has become a daily issue, whose complexity is constantly rising. Urban growth has increased the demand for limited infrastructure of transportation, including streets. In order to smooth the traffic flow, there are two approaches to infrastructure development and the efficient and maximum use of limited resources (streets). In this paper, the second approach is taken into consideration; (correct use of existing resources) and misuse of these resources will waste time.

A. Transportation network and traffic control system

The transportation network consists of four main attributes that are linked to the traffic system.

- 1- Road users: drivers, passengers, pedestrians and...
2. Vehicles
3. Roads, streets and freeways and...
4. Traffic control tools

The traffic control system consists of a traffic network (including streets, highways and freeways), sensors, monitoring, control strategy and control devices. Traffic control allows limited road infrastructure to continuously operate at its maximum optimal capacity. This will increase the productivity of existing facilities.

B. Intelligent transportation system

Traffic congestion is caused by population growth, urbanization and an increase in the number of vehicles, which reduces the efficiency of transportation infrastructure, travel time, air pollution and fuel consumption. Today, various strategies are used to control urban traffic. The Intelligent transportation system plays a huge role in modern life and has a profound impact on the economy of the country, the environment and lifestyle. The Intelligent Transportation System (ITS) refers to the application of hardware and software technologies to reduce transportation problems. ITS includes all areas of information technology used in transportation including control, computing, communications, algorithms, databases, models, and human interfaces. The emergence of these technologies is considered as a new way of solving transport problems. The benefits of ITS can be considered in terms of reducing accidents, reducing travel time and increasing the efficiency of existing resources. The ITS is a system divided into two intelligent infrastructure and intelligent car subsystems, according to the US Department of Transportation.

Intelligent vehicles or unmanned vehicles are the right names for cars with such capabilities. The chosen name for these vehicles is not different in the way they are used and the technologies used in them; so that all produced models try to

reduce or even eliminate the human agent's involvement in driving the car and delivering all the decisions and processes of driving the car to computers embedded in cars or external vehicle control systems [2].

In this article, we call a vehicle intelligent that lets you send information such as geographic location, source, destination and route to a control center using communications such as cellular networks or wireless communications; You can receive information from the control center system and proceed with it.

C. Different components of the traffic control system

- 1- Traffic network
2. Sensors
3. Monitoring system
4. Traffic control approach
5. Traffic control equipment
6. Disturbances

D. Sensors and actuators

Traffic cameras and induction rings are one of the most important traffic sensors. Traffic cameras are used to detect queue lengths at intersections and Monitoring applications, while at the same time low resolution is a disadvantage of cameras. Induction rings can be a type of traffic counter system. By passing vehicles above or near it, they have the ability to count, classify and record vehicle speeds and measure vehicle length with appropriate approximation [4].

By utilizing actuators such as traffic lights, intersections capacity and proper operation conditions of the intersections can be increased. On the other hand, installing them will cause cost and delay in the system. There are important parameters in the traffic light, which requires proper knowledge of these parameters in order to use the traffic light.

- Phase: The sum of the green traffic light time and the time consumed (including the lights in yellow and all red).
- Cycle: total time of all phases. To deal with interference currents in successive phases, there should be a fixed interval of several seconds for evacuation of the intersection.
- Split: The green or red lights time are green or red split respectively.

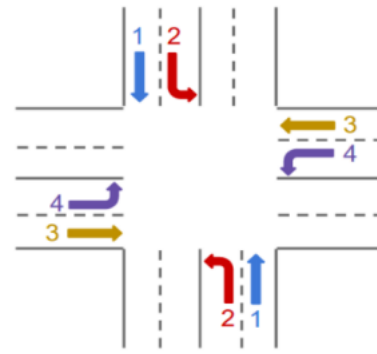


Figure 2. An example of a traffic light with four phases

There are several lines in intersection, and each of these lines is either simultaneous or non- simultaneous. For example, if the two distinct lines 1 and 1 (blue) concurrently enter the intersection in Fig. 2, they are simultaneous. In the same fig, four simultaneous flows are 1, 2, 3, and 4. Each of the traffic lights can have different phases depending on the type of intersection and the number of simultaneous flows.

E. Traffic control methods

Traffic is a well-known international term, and is referred to in the laws as the collection of vehicles and persons passages on the road. Different methods can be used to control traffic as shown in Fig. 3 [4][9].

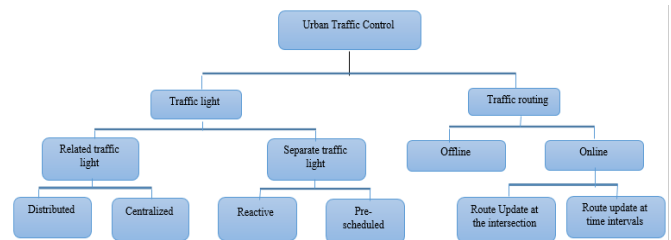


Figure 3 Classification of urban traffic control methods

1) . Types of traffic routing

In the implementation of traffic routing, there are two types of online and offline routing that are also referred to in some studies as static routing and dynamic routing. In offline routing, a fixed route for cars is calculated at the beginning of the travel, and this route remains fixed until the vehicle reaches the destination, and after selecting the route, the new traffic conditions do not have an effect on routing. In online routing, traffic information is immediately provided to the decision-making system, after moving cars on the route, traffic changes are transmitted online, and the routing algorithm available on the system sends the required response based on changes and requests available.

III. HISTORY OF TRAFFIC MANAGEMENT AND CONTROL SYSTEM

When the IBM 650 computer was first introduced in 1959 for the urban traffic management system, the phenomenon of traffic control and management was equivalent to the phenomenon of computing in the field of information technology. According to research conducted in [10] this history, divides the system into five distinct stages, which are reflected in five stages of deployment of traffic control and management pattern. Firstly, computers were very large and costly, so large computers were usually shared between multiple terminals. In 1960, the traffic management system shared the resources of a centralized computer.

With the arrival of large-scale integrated circuits (LSIs) and shrinking computer technology, the IT industry was entering the second transformation in the calculation model. At this point, microcomputers were powerful enough to meet the computational needs of a user. At that time, similar technologies triggered the emergence of a Traffic Signal Controller (TSC). Each TSC had enough storage capacity and independent computing to control an intersection. During this period, researchers optimized control models and TSC parameters to improve control. TRANSYT was one of the traffic control systems at this stage, which included multiple control points.

Thirdly, local area networks (LANs) came to share resources and meet the complex needs of the phenomenon. Ethernet is one of the frame-based technologies for local networks, which was established in 1973-1975, and Ethernet was widely used from that time on. During this period, urban traffic management systems used the benefits of LAN technology to develop a hierarchical model. Network connections made it possible for the layers to perform their tasks correctly when working with other layers.

In the fourth stage, in the age of the Internet, users were able to receive data from sites and process them locally, calculations based on agents and mobile agents were introduced in this period. The important features of the agents are the ability to perform close-to-data computations, which can improve system performance by reducing communication time and costs. Other solutions that the agents were able to succeed were the ability to negotiate between agents to control the operating strategies.

Since 2000, the IT industry has been merged into a new concept called cloud computing. Cloud computing is based on the Internet and provides the individual and business needs in a heterogeneous and automated service as needed. By using cloud computing, users are served without knowing about the infrastructure, and only based on what source they need. In recent years, Parallel transportation Management Systems (PtMS) research and programs have been

implemented. These studies include artificial systems, computational experiments and parallel implementation, which are the focus of attention in traffic research [11]. Although exact construction or testing of some systems is very complicated or even impossible, PtMS used an artificial transportation system (ATS) to compensate for this defect.

According to studies conducted in [12], it is possible to store and process big data at the right time with the presence of IOT along with cloud computing. This feature of cloud computing improves decision-making speed and ultimately decision-making in the shortest possible time for managing and controlling urban dynamic traffic.

IV. SYSTEM DESIGN

This section examines the proposed method for improving traffic flow in the city. To perform any analysis and estimate the traffic situation, one must first collect traffic data in the city. The data is collected using sensors located in the city. Consider the road transport network as a weighted graph of the edges and nodes. In this graph, edges are equivalent of the street and the nodes are equivalent to the intersection. In most studies, travel time in the street is considered as the weight of the edges. One of the speed and time travel calculation models is the Greenshield model, which uses a linear relationship between traffic density and estimated speed, and can be used to calculate travel time per street. Assuming the use of IOT technology and information on the direction of the movement of vehicles, the time of traffic lights, the remaining capacity of the streets, we present a new model to predict travel time for each of the streets. After identifying the potential for congestion on each street, how to choose cars for re-routing is important so that this selection method prevents congestion and prevents congestion elsewhere. In the following, we present a method for this purpose and finally, we propose a method for selecting the shortest route with Dijkstra method based on dynamic weighing algorithm, so that route selection for a car will directly affect the choice of the next-cars route. The framework presented in Figure 4 shows the performance of our proposed approach.

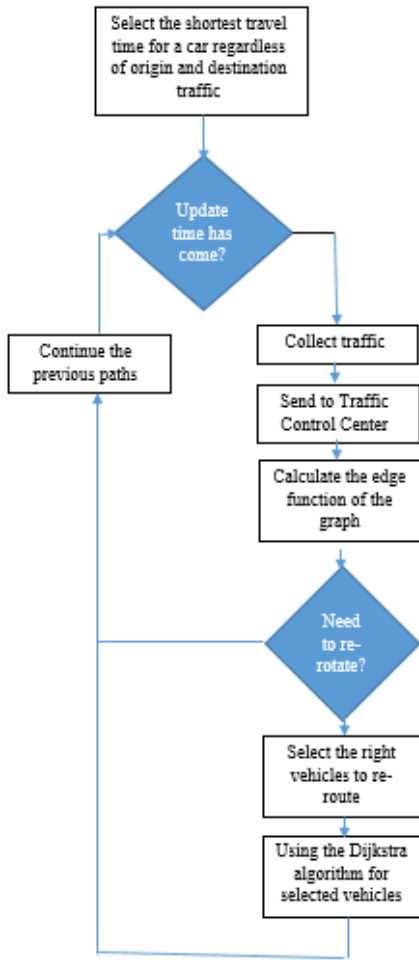


Figure 4 the general framework of the proposed method

A. Traffic data Estimation

We considered the road transport network as a graph of the edges (E) and nodes (N). The cars move inside the edges, and as the congestion increases, the speed of the cars is also reduced. Each of the Edges has a weight and weights are the estimated travel time at the desired edge. Weights are calculated periodically and are available. There are various ways to estimate road travel time. You can use GPS based data storage devices, GSM based on vehicle traffic data (FCB) and Bluetooth [7]. One of the methods for estimating the Greenshield travel time is a linear relationship between traffic density and estimated speed. This method has been used extensively in the models of transportation researchers. In [13], the Eq. (1) is expressed:

$$V_i(k) = V_f \left(1 - \frac{X_i(k)}{X_{jam}}\right) \quad (1)$$

$$T_i(k) = \frac{L_i}{V_i(k)}$$

In Equation (1), X_{jam} is the maximum capacity on the i -th street, $X_i(k)$ is the traffic volume of the i -th street at the time interval k , V_f is the free flow velocity on the i -th street, L_i ,

and $T_i(k)$ are the length of the i -th street. And the estimated travel time on the i -th street in the time interval k , respectively.

Basically, $\frac{X_i}{X_{jam}}$ is the ratio of the average number of

vehicles currently in the street and the maximum capacity of streets, the number of cars on the street can be collected using various technologies for collecting traffic data. The maximum number of vehicles in the streets is calculated according to Eq. (2).

$$X_{jam} = \frac{\text{road's length} * \text{number of lane}}{\text{average of vehicle length} + \text{min gap}} \quad (2)$$

In the proposed model, for calculating travel time in the edge, the effect of the downstream edges on the upstream edges has not been applied. For example, if the downstream edge capacity is much less than the upstream edges, after filling the edge there is no possibility of entering the car from the upstream edges to this edge, also how many cars cross the intersection in the upstream edge when the light is green. how should we calculate travel time for cars? In the new method for calculating the cost function, this problem is considered, as shown in Eq. (3).

$$F_i(k) = T_i(k) + H_i(k) \quad (3)$$

Initially, the maximum output flow from the edge i to the downstream edge $(i+1)_d$ in which the traffic flow enters, during the green light of the traffic light and at the time interval k indicated by $S_{i \rightarrow (i+1)_d}(k)$. From equation (4) we estimate this value.

$$S_{i \rightarrow (i+1)_d}(k) = \frac{T_{i \rightarrow (i+1)_d}^{green}(k)}{\text{saturation headway}} \quad (4)$$

The time interval between two vehicles in saturation mode in the transport system, according to equation (5), is usually considered to be 1.9 seconds.

saturation flow rate=1900 vehicles/hour/lane=0.53 vehicle/second/lane

$$\text{Headway} = \frac{1}{\text{saturation flow rate}}$$

$$\text{Headway} = \frac{1}{1900} * 3600 = 1.9s$$

(5)

The maximum cycle and the maximum time required to evacuation of the i -th street are obtained from Eq. (6) and (7), respectively.

$$N_i(k) = \underset{d=1}{D_i} \text{Max} \left\{ \text{Max} \left\{ \frac{X_i(k) * \gamma_{i \rightarrow (i+1)_d}(k)}{\left(X_{jam_{(i+1)_d}} - X_{(i+1)_d}(k) \right) + 1}, \frac{X_i(k) * \gamma_{i \rightarrow (i+1)_d}(k)}{S_{i \rightarrow (i+1)_d}(k)} \right\} \right\} \quad (6)$$

$$H_i(k) = T_{cycle, i \rightarrow (i+1)} * N_i(k) \quad (7)$$

- $X_i(k)$: The traffic volume detected on the i-th street at a time interval k
- $\gamma_{i \rightarrow (i+1)_d}(k)$: The ratio of traffic split on the i-street, entering the downstream street d at k.
- $X_{jam_{(i+1)_d}}$: The maximum capacity on downstream street d from street i
- $N_i(k)$: Maximum cycle required for evacuation of i-th street
- $T_{cycle, i \rightarrow (i+1)}$: The duration of a cycle for the i-th street
- $H_i(k)$: The time needed to evacuate the i-th street
- $F_i(k)$: The cost function of the travel time of a car arrives until it leaves the street
- $T_i(k)$: The estimated travel time in the i-th street within the period k.

Considering 1- the number of cars on the i-th street, 2. Knowing what percentage of the vehicles in the street intend to enter each of the downstream streets; 3. The saturation capacity of the intersection; 4. The remaining capacity of the downstream streets and using Eq. (4-7), one can calculate the new travel cost function for each of the streets. Based on the new cost function, each of the selected vehicles is re-routed.

B. Congestion Detection and prediction

The proposed system assumes that cars are accessible through the Internet through the central system and all information, including the source and destination of vehicles, is available. Also, periodically, traffic data, such as traffic volume per street, is collected through the sensor in the network every second and sent to the central system, which k represents the traffic control intervals. Based on the instantaneous traffic data collected, if $\frac{X_i(k)}{X_{jam_i}} \geq \delta$, the i-th street shows the congestion signs. $\delta \in [0,1]$ The threshold for congestion and X_{jam_i} is the capacity of the i-th street.

C. Vehicle selection method for re-routing

When the possibility of congestion is detected on a part of the road network, the removal of vehicles whose routes include the street in question, can reduce traffic congestion in that area. One can use the parameter L to decide on the choice of cars, the distance from the congested street to be re-routed, which also reduces traffic congestion, that is, the cars are suitable for routing that located up to L steps above the congestion point. We have to choose an L in order to have the best result. If the value of L is more than a threshold, the selected vehicles can increase to such an extent that traffic congestion can be generated elsewhere. For L, we test the values of 1, 2, 3, and 4 in the simulation. That is, cars that are 1, 2, 3 or 4 streets above the congestion point and their route passes from the point of congestion are selected for re-routing. The results show that how much L is greater than 2, the results get worse and the average travel and waiting time increases.

D. Set traffic light

In this section, we will use Adaptive Traffic Control with intersections' sensors. In each case, several lines are entered, and each of these lines is either simultaneous or non-simultaneous. If the two distinct lines vehicles simultaneously enter the intersection, the two lines are simultaneous. In Fig. 2, four simultaneous groups are shown. The time the traffic light is green to cross a simultaneous group, plus the time consumed (including yellow and all red) is called the phase. The total time that all groups spend a phase is called a cycle. Each of the traffic lights can have different phases depending on the type of intersection and the number of simultaneous groups. In this study, we also added the minDuration and maxDuration components for dynamically adjusting the traffic lights phases. By default, the time of each phase is set to minDuration. the sensor is placed At detector-gap = 2m distance to detect the car; if, after the minDuration time has elapsed, the sensor does not detect any vehicle, the traffic light enters the next phase, otherwise max = gap = 3s is added to The time of the phase and this may continue until maxDuration.

E. Select the route of the proposed method

After calculating the travel cost using the cost function derived from Section 1.4, the routing with the proposed PDDVRF method is explained below.

1) Routing with Dijkstra Algorithm Based on Dynamic Weighing

This algorithm is a modified Dijkstra algorithm that influences the routing of a car on other vehicle routings, which is labeled PDDVRF. In previous methods, if drivers choose the same route in the next window, there will be potential for congestion in the selected routes. Assuming that all drivers share the chosen route, in this algorithm there is a possibility for the system to use the footprint of each of the

routed vehicles for future routing and to avoid congestion that may be created in the future.

For each street i , n_i is the number of vehicles whose route includes street i . The f_{ri} is the i -th street weighted value of cars that intend to cross and equals to $f_{ri} = \frac{n_i}{X_{jam_i}}$. The larger

the f_{ri} , the greater the probability of a congestion in the desired street; therefore, streets with greater f_{ri} should not be used for future routes as far as possible. We used X_{jam_i} to differentiate according to the characteristics of the streets. Suppose $n_i = n_j$ for both streets i and j . If the capacity of the i -th street is greater than the j -th street, the traffic flow on i -th street will be smoother than the j -th street and less likely to be congested. Finally, for each street, the cost function is calculated according to Eq. (8):

$$F_{ri}(k) = F_i(k) * (1 - \zeta) + f_{ri}(k) * \zeta \quad (8)$$

ζ : Weighting factor

• $F_i(k)$: The cost function obtained from equation (3)

• $F_{ri}(k)$: Cost function considering dynamic weighting

V. SIMULATION

SUMO 0.24.0 and TraCI have been used for simulation. SUMO is a microscopic, portable, open source wireless simulation suite designed for large road networks. TraCI is a library that provides simulation behavior control commands such as vehicle status, road settings, and traffic lights. The routing algorithms and the dynamic settings for traffic lights have been made through this library using Python programming. You can use the OpenStreetMap (OSM) [14] to use the city streets map in the SUMO simulator. OSM is a complete city map of the world that has been completed and updated by many people using aerial imagery, GPS devices, and etc. After downloading the map through OSM, using the Netconvert OSM files are converted to files used by SUMO. using Netconvert, one can remove railways, tunnels, bus routes, etc. from the map, and specify speed limits for the streets. In this study, we used the Brooklyn Urban Map and the Roadmap for Penn et al. [13] to compare with other methods. Brooklyn, one of the five New York districts with an area of 77.85 square kilometers, 155.55 km streets length, 192 intersections and 551 streets. . With simulations, we compare the performance of our method with other strategies.

The Brooklyn Road Traffic Flow Map is shown in Figure 5. There are 1,000 vehicles in the Brooklyn network that start moving from the left to the right of the network in the zero to 1000 second range. In Table 1, the parameters used in simulation are introduced. Also, to compare results for low

traffic and high traffic modes, simulations have also been done with 1500, 2000, and 2500 cars.

Table 1. Parameters Used in Simulation

Parameter	Definition
Frequency	Time interval to predict and re-route 120,250,350,450
Congestion threshold δ	If $\frac{x_i(k)}{x_{jam}} > \delta$ the street is congested in k -th time interval. $\delta=0.6$
Level	Network depth from the congestion location which used to select vehicles to re-route $L=1,2,3$

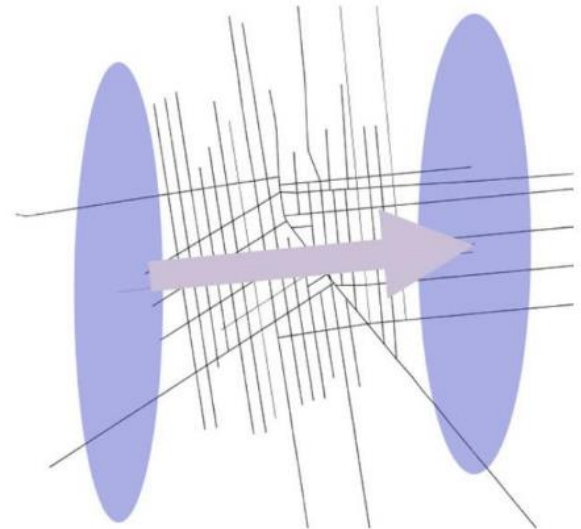


Figure 5 Traffic Flow on Brooklyn Road Network [13]

A. Simulation settings

In this section, the proposed method for improving traffic conditions is evaluated. First, the urban network traffic specifications are described. After identifying areas where congestion is likely to occur, car choices are made using its parameters. Using the proposed model, the cost of the graph edges is calculated and cars are routed using the proposed PDDVRWF method. Finally, the results of the proposed method in this paper are compared with other proposed methods in the research.

In simulations, we used default settings in Sumo. The length of the cars is 5 meters, the minimum distance between the

cars is 2.5 meters, the vehicle following model is Krauss [15], acceleration is $2.6m/s^2$, and defect and driving error is 0.5. With the observations obtained from the simulator, the average travel time of an vehicle from an intersection per line is 2 seconds. Using the Python programming language and TraCI library, we communicated with the SUMO simulator and sent the commands to the simulator based on the data collected.

B. Different scenarios with static traffic lights

Various parameters affect traffic control management. The use of any of the parameters alone can have a positive or negative effect on the traffic situation. By simultaneously taking into account several parameters, recognition of the environment is possible, and better decisions can be made. Regarding the static traffic light in [13], we used static traffic light for a fair comparison. Using the new cost function, we examined the average vehicle travel time in the city with several different car volumes in the streets to compare the performance of the proposed algorithm with a low traffic and high traffic network with other methods. We also calculated the average number of re-routing and average wait times. Sampling and control times affect simulation results. The less sampling and control times are, the faster the city traffic information is obtained, and better decisions can be made. With increasing sampling time, decisions are made more slowly, and by deciding too late, many vehicles will not be able to reach the right route. In the next section, Different values of the sampling time parameter are applied to the simulation and the results are analyzed.

In the proposed PDDVRWF method, the vehicle's routes are effective in predicting the traffic situation of the streets. As the name of a street goes up in the car's route, the traffic is likely to increase on the street and will increase the cost. This makes it possible to choose another route for future vehicles. This will prevent congestion at the streets of the city.

C. Average travel time

One of the criteria for assessing the system is the average travel time of cars. Table 2 and Figure 6 show the results of the proposed method and research methods [13]. Estimates of average travel time is done taking into account different traffic volumes, for 1000, 1500, 2000, and 2500 cars in simulation.

In the DSP method [13], after observing each congestion, all vehicles that intend to cross the congestion point are selected for routing. If many of these cars do not need to be re-routed, this can even moves congestion from one point to another. For this reason, the average time taken by the DSP method is greater. RKSP, EBKSP, and FBKSP [13] routings are the same for a set of vehicles with the same source and destination. Several routes are calculated for the source and destination, and each path is randomly, entropy and flow-based, allocated to one of the vehicles, respectively. The

comparison of the average travel time between DDVR and DSP demonstrates a better performance of the DDVR method. Also, the DDVR method is better than RKSP, EBKSP, and FBKSP. In AR * method, when vehicles are routed using the A exploratory algorithm, car routing affects other vehicles, results in better results than the DDVR method.

Table 2. Comparison of average travel time with other methods at L = 2 and $\tau = 450$

PDDVR WRF	DD VR	R*	F BKSP	E BKSP	R KSP	SP	Number of vehicles
1356	1617	1480	1685	1620	1750	1820	V.No.=1000
1597	1881	1700	1920	1910	2100	2240	V.No.=1500
1709	1932	1790	2180	2150	2360	2480	V.No.=2000
1822	2174	1895	2290	2190	2490	2510	V.No.=2500

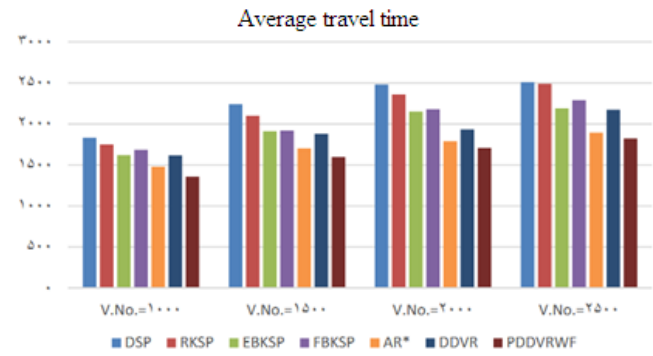


Figure 6 Comparison of average travel time with other methods

The PDDVRWF method operates using the Dijkstra algorithm based on the new cost function, in which the street weights vary with each routing according to the capacity of that street. This method has achieved an average travel time better than other methods. Due to the fact that the routing of each car affects the weight of the city streets, later vehicles will be routed with these changes, which will lead to better routes for future vehicles.

Table 3. Comparison of the average travel time with the change of vehicle selection level and different traffic volume $\tau = 450$

L=3		L=2		L=1		Number of vehicles
PDDVRWF	DDVR	PDDVRWF	DDVR	PDDVRWF	DDVR	
1399	1642	1356	1617	1318	1629	V.No.=1000
1659	1884	1597	1881	1522	1872	V.No.=1500
1829	1937	1709	1932	1747	2105	V.No.=2000
1854	2246	1822	2174	1899	2207	V.No.=2500

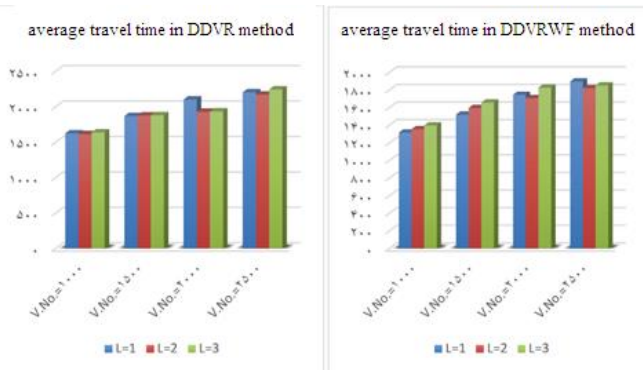


Figure 7 Average travel time results by varying vehicle selection levels and traffic volumes

Several simulations were performed with different values of the L parameter. The average travel time results in Table 3 and Fig. 7 show that the average travel time obtained for L = 2 is lower than the other values of L. When the congestion signs appear on a street, it is necessary to prevent the arrival of vehicles that are intended to enter the specified street in the next window to avoid more severe congestion. Now, for cars that are at a higher level than the street, there may no longer be any need for a redirection, and there will be no congestion in the next windows of the street. The results show that in the DDVR method after the identification of congestion signs, if the level $2 < L$ is considered, the average travel time results for cars will increase. In the PDDVRWF method, for every routing, the effect of all cars has been taken from the beginning. For the city with low traffic volume, the choice of car from the first level shows better results, but with increasing traffic volume in the city, the average travel time is lower choosing a car to the second level. This shows that urban traffic can be one of the factors affecting the L-level and choosing a car. It should be noted that in all simulations for comparison, $\tau = 450$ s is considered according to the default value.

Sampling time is one of the important parameters that has been evaluated in this research. The shorter the sampling time, the more information is collected at smaller intervals. A quick decision can prevent congestion; it will have a better impact on the performance of the system and will reduce the travel time.

In Table 4 and Figure 8, the simulation is repeated for different t and $l = L$, which shows that as τ decreases, the average travel time for all cars is reduced. Of course, no matter how much the τ value is reduced, the calculations performed by the decision-making system increase. With regard to available equipment and facilities, a balance can be considered at the time of sampling and the average travel time.

Table 4. Comparison of the average travel time with the sampling time changes and $L = 1$

$\tau = 450$		$\tau = 300$		$\tau = 150$		$\tau = 120$		
PDDVRWF	DDVR	PDDVRWF	DDVR	PDDVRWF	DDVR	PDDVRWF	DDVR	
1318	1629	1281	1583	1264	1476	1229	1412	$V.No.=1000$
1522	1872	1526	1902	1519	1829	1499	1770	$V.No.=1500$
1747	2105	1691	2081	1718	2004	1656	1998	$V.No.=2000$
1899	2207	1766	2223	1797	2162	1776	2130	$V.No.=2500$

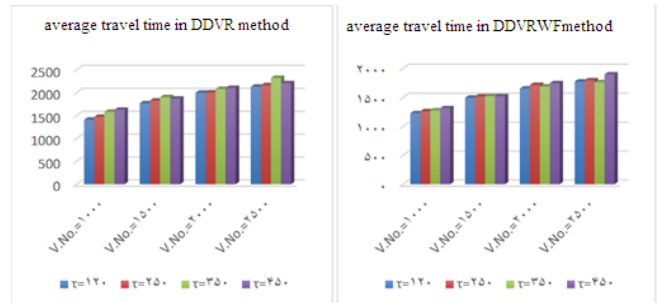


Figure 8 Average travel time results by varying vehicle selection levels and traffic volumes

D. Average waiting time

Staying in traffic and waiting behind the trains of vehicles that stand still for a long time is a situation that we all experience almost every day. One can consider the waiting time as another urban traffic criterion. The shorter the waiting time for cars in the streets and behind the intersections indicates the smooth traffic flow. In simulation, we have considered the speed of the car below 0.1 m / s as a wait or stop mode. Table 5 and Figure 9 show the comparison of waiting times for different values of L. By choosing the right level of L, one can reduce the travel time and the waiting time.

Table 5. Comparison of the average waiting time with regard to changes in sampling time

$\tau = 450$		$\tau = 300$		$\tau = 150$		$\tau = 120$		
PDDVRWF	DDVR	PDDVRWF	DDVR	PDDVRWF	DDVR	PDDVRWF	DDVR	
806	1039	779	1023	754	915	709	840	$V.No.=1000$
958	1276	956	1253	942	1172	906	1093	$V.No.=1500$
1123	1404	1064	1388	1067	1305	1001	1226	$V.No.=2000$
1219	1477	1097	1491	1104	1397	1077	1331	$V.No.=2500$

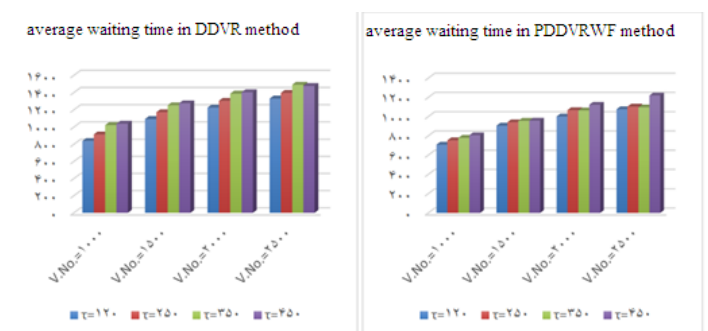


Figure 9 Average waiting time with sampling time changes

E. Different scenarios with dynamic traffic lights

In dynamic control of traffic signal, input information is collected from the indicator. An indicator can be a set of sensors that determine the presence or absence of a car on the street. Given the presence or absence of a car on the street, the controller can give more time to the lights indicating the presence of traffic; or it announces a phase change command indicating a lack of traffic.

The comparison of the average travel time of the proposed DDVR method in static and dynamic traffic signal modes is shown in Fig. 9, the travel time for a mode with dynamic traffic lights is much less than static. Travel time is improved from 20% for 2000 and 2500 cars to 28% for 1,000 vehicles.

The results of the proposed PDDVRWF method shown in Table 6 and Figure 10 indicate the importance of dynamic traffic lights, as in the previous approach. So that for 2000, 1500, 1000 cars was reduced by 30% and for 2500 vehicles, a 22% reduction in travel time was achieved.

Table 6. The results of the average travel time of the PDDVRWF method for static and dynamic traffic lights

dynamic traffic light	static traffic light	number of vehicle
929	1318	V.No.=1000
1056	1522	V.No.=1500
1227	1747	V.No.=2000
1481	1899	V.No.=2500

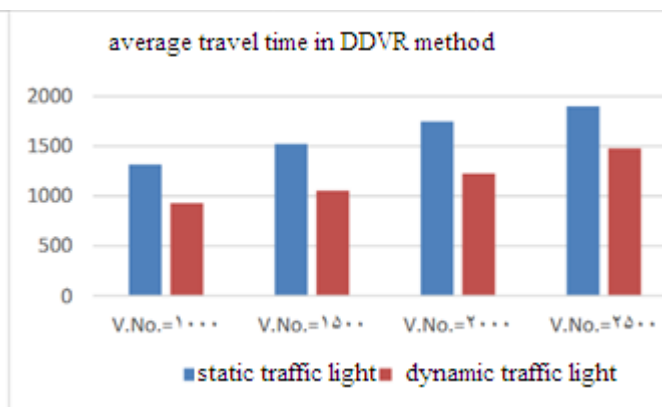


Figure 10 Average time in PDDVRWF method for static and dynamic traffic lights

In the following, the average waiting time is compared for both static and dynamic traffic lights. The results for the DDVR and PDDVRWF methods for the different traffic volumes are shown in Table 7 and Table 11.

Table 7. Average DDVR waiting time for static and dynamic traffic lights

dynamic traffic light	static traffic light	number of vehicles
655	1039	V.No.=1000
815	1276	V.No.=1500
1026	1299	V.No.=2000
1091	1453	V.No.=2500

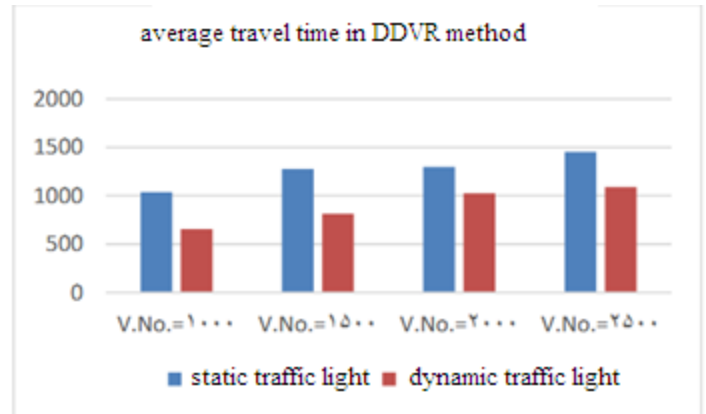


Figure 11 Average DDVR waiting time for static and dynamic traffic lights

Table 8. Average waiting time results of PDDVRWF method for static and dynamic traffic lights

dynamic traffic light	static traffic light	number of vehicles
463	809	V.No.=1000
546	958	V.No.=1500
664	1123	V.No.=2000
857	1219	V.No.=2500

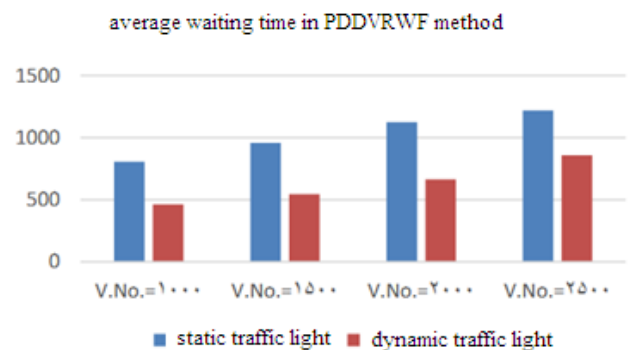


Figure 11 Average waiting time in PDDVRWF method for static and dynamic traffic lights

In the case of dynamic traffic lights, due to the successive change in the green time in each phase, the maximum output flow in equation 4 cannot be accurately calculated, which could affect the prediction of the cost of each street, and the calculations can be inaccurate. Although the results obtained in dynamic traffic lights indicate improved performance.

VI. CONCLUSION

In this paper, a new travel cost calculation method was presented and the values of the cost function were used to calculate and re-rotate the cars by the central system in order to reduce the average travel time. After identifying the potential for congestion in the streets, we considered several levels of upstream streets. In selected streets, we select vehicles whose route includes a high traffic street to be re-routed. Then, in this paper, we evaluated suggested methods for managing and controlling urban traffic using dynamic allocation of paths to vehicles. Using the new cost function, we also used Dijkstra method, a shortest route selection method based on dynamic weighing algorithm. In this method, the routing of a vehicle influences the routing of other vehicles, and it is possible for the system to use the footprint of each of the routed vehicles to route other vehicles and prevent future congestion. In the proposed PDDVRWF method, after simulating the results showed that using better prediction of future street traffic conditions, results are obtained better than the previous DDVR method. Comparing the results of the two identical routing methods with the difference in the dynamic and static traffic lights showed the excellent performance of dynamic traffic lights. The simultaneous use of dynamic routing and dynamic traffic lights can improve traffic flow in the city.

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