User-based Vehicle Route Guidance in Urban Networks Based on Intelligent Multi Agents Systems and the ANT-Q Algorithm

Alireza Eydi[1], Susan Panahi[2], Isa Nakhai Kamalabadi[3]

Abstract

Guiding vehicles to their destination under dynamic traffic conditions is an important topic in the field of Intelligent Transportation Systems (ITS). Nowadays, many complex systems can be controlled by using multi agent systems. Adaptation with the current condition is an important feature of the agents. In this research, formulation of dynamic guidance for vehicles has been investigated based on the characteristics of ITS and using the user-based approach to meet drivers' satisfaction. As a result of time-varying flows on traffic networks, a multi agent model and the routing algorithm based on artificial intelligence techniques emphasized on a hybrid algorithm combining Ant Colony and Reinforcement Learning is proposed. The critical result of this paper is the ability of designing an algorithm for better trip planning, routing decisions in a dynamic urban transportation. Finally, the validity of the proposed algorithm is shown by implementation on a sub-network extracted from Tehran traffic map.

Keywords: urban transportation network, route guidance, ANT-Q algorithm, Intelligent Agents, user-based system

Corresponding author E- mail: alireza.eydi@uok.ac.ir
1. Assistant Professor, Faculty of Engineering, University of Kurdistan, Sanandaj, Iran
2. MSc. Grad., Department of Industrial Engineering, , Tarbiat Modares University, Tehran, Iran
3. Professor, Faculty of Engineering, University of Kurdistan, Sanandaj, Iran

1. Introduction

Nowadays, increasing numbers of vehicles to transport goods and passengers have caused congestion in transportation networks, especially in big cities. Congestion leads to losing time, energy, and damaging to the environment and health. Building new roads and other transportation facilities is extremely costly and has to overcome shortages of space. On the other hand, due to a lack of experience or a lack of accuracy in predicting traffic conditions in addition to the unfamiliarity of drivers (especially private vehicles) with various route alternatives with respect to existing facilities, cannot select optimal routes based on various criteria. The result is increasingly complex trips. Hence, one of the main challenges in the development of a traffic network is guiding vehicles to their destination in dynamic traffic conditions, with the aim of reducing costs, such as travel time and more efficient use of available network capacity. So, in order to avoid traffic congestion and make travel easier, drivers need reliable traffic guidance. Traffic guidance is the proper distribution of traffic flows on all traffic network routes [sadek and Chowdhury, 2003; Levinson, 2003].

In general, in order to solve this problem, dynamic guidance systems seem to be an effective approach. Dynamic route guidance systems that are based on information and communication technologies are important in the area of Intelligent Transportation Systems (ITS) activity. Information and communication technologies, such as sensor technology and wireless communication systems, are low-cost with high reliability. The main core of a dynamic route guidance system is calculating the shortest path computation in dynamic networks. By using real-time data (online), such as speed and density, the system is able to identify and recommend the shortest path from origin to a destination based on the user and driver's current position. Therefore, while upgrading the utility of existing transportation infrastructure, travel costs to drivers is minimal. To be effective, it is also largely dependent on shortest path algorithms. Obviously, static approaches (or offline approaches), such as Dijkstra's algorithm, have disadvantages such as a lack of adapting to network conditions. The system is also able to inform drivers about network conditions. This information is usually obtained via variable message signs (VMS) or vehicle displayers [Adler and Blue, 1998; Deflorio, 2003; Vandebon and UPadhyay, 1997]. The user-based approach is also another aspect of ITS. This means that the goals and demands of the users (or drivers) such as time-saving or fuel-saving need to be considered. However, in many routing issues, the user rather than a target (or criteria) pursues several targets, which are occasionally in conflict with each other. Selecting the appropriate criteria and defining the importance of each one depends on the user's preferences (i.e., some drivers who are interested in high-speed movement). Therefore, routing algorithms are mostly able to meet several goals simultaneously and offer routes with the highest value.

As a result of the difficulty of calculating the dynamic shortest path is a key driver for research in finding alternative ways of developing computational algorithms to find the optimal solution path that provide good estimates of optimal answers and reduces computational implementation. Furthermore, literature in routing area problems is quite extensive, thus we limit our review to the most relevant issues in three areas: (i) dynamic routing & traffic control (ii) heuristic algorithms in route guidance (iii) multi-agent systems in dynamic vehicle routing.

(i): Papageorgiou et al. (2003) focus on the problem of traffic control, briefly reviewing route guidance strategies. Schmitt and Jula (2006), in their reviewed paper, enumerated and explained the features of static and dynamic, deterministic and probabilistic, reactive and anticipatory, centralized and decentralized route guidance systems. Dong (2011) reviewed literature related to route guidance systems in detail, including the main components of such systems and the procedures. Many studies have been conducted on dynamic route guidance systems, including Karimi et al. (2004), Yamashita et al. (2004) and Wunderlich et al. (2000). In addition, Fu (2001) presented a system based on dynamic routing of the shortest path problem. Wu et al. (2008) used a

new dynamic traffic model to determine the route used by the drivers. Nadi and Delavar (2010) presented a model for routing planning uses in real-time traffic data, acquired by the sensors. Lee (2006) offered a modified Dijkstra's algorithm to be used in a vehicle navigation system. Some researchers, such as Niaraki Sadeghi and Kim (2009), as well as Nadi and Delavar (2011) have examined the preferences of the users in navigation systems.

(ii): Park et al. (2007a) developed heuristic algorithms to identify a manageable subset of near-optimal routes (multi-path) for the online routing of vehicles. Park et al. (2007b) examined an adaptive route guidance system with the use of learning algorithms to predict which route should be selected. Furthermore, a comprehensive overview of different heuristic shortest path algorithms has been conducted by Fuet et al. (2006). Some researchers also use meta-heuristic algorithms for finding near optimal solutions of the shortest path problem. Pahlavani et al. (2006) examined the problem of Multi Criteria route guidance in urban networks, and offered a new approach based on genetic algorithms and geographic information systems. Pahlavani and Delavar (2014) in their study analysed some approaches of neuro-fuzzy through conducting preferences of the drivers to evaluate and design multi criteria route planning in urban transportation networks. Gu et al. (2010) presented a community-based approach of ant colony optimization for solving the shortest paths problem in dynamic route guidance. The results of simulation experiments showed the effectiveness of the proposed algorithm. Yoshikawa and Otani (2010) also proposed a new algorithm that combines tabu search and ant colony optimization. Masoomi et al. (2011) used multi-objective ant colony algorithms, which change in contrast to the structure of the one objective algorithm, for developing a user-based routing algorithm. The researchers tried to implement one of the ITS properties that focus on user wishes.

(iii): Other approaches to solving complex problems, such as route guidance systems using the multi agent system approach to improve the management and coordination of traffic networks [Martiet et al. 2009]. Chen and Cheng (2010)

reviewed the applications of agent technology in traffic and transportation systems. Adler and Blue (2002) suggested a multi agent system approach for vehicle routing and scheduling, and propounded that vehicles can be modelled as mobile agents. Moreover, Chabrolet et al. (2006), in their study, use the multi-agent approach to modelling and solving urban traffic systems. Cai and Yang (2007) study urban traffic management based on multi agent systems in the field of intelligent traffic management. Shi et al. (2008) studied the feasibility and applicability of route guidance systems based on a network of agents that can automatically guide vehicles. Claes et al. (2011) presented a decentralized approach for anticipatory vehicle routing that is based on delegate multiagent systems. Ng et al. (2013) evaluated and reviewed intelligent control methods for intersections and freeways, such as adaptive control, model-based and agent-based approaches, for use in driver information and route guidance systems.By using agents, the current traffic conditions are reported and by using the multi agent systems, the shortest path to a given destination is calculated, as demonstrated in the investigations of Che et al. (2009) and Zolfpur et al. (2011). Cao et al. (2016) proposed a decentralized multi-agent approach, where infrastructure agents locally collect intentions of concerned vehicle agents, to guarantee their arrival on time.

With the introduction of new computational methods, such as reinforcement learning, the optimal solution can be searched faster, which is used in cases such as extraction of optimal control policies at intersections [Jiongand and Zhao, 2011]. Nakhai and Eydi (2009) explained the application of agent-oriented techniques by providing a description of a conceptual framework of the routing problem based on a decentralized routing problem structure, with an emphasis on learning as a solution in the face of uncertain routing in the traffic network.

According to the challenges and needs behind this research project, the research can be defined in terms of efficient and flexible routing strategies that be affected in driver decision-making, using real-time traffic data, in order to guide vehicles in dynamic environments. Therefore, as this study

aims to consider the socio-economic realities and a more complete description of traffic conditions, a formulation of the dynamic vehicle routing problem based on ITS features aimed at satisfying drivers will be conducted. Furthermore, due to the time varying nature of traffic networks and due to changes in traffic conditions, vehicle route computation for reaching a destination most effectively is calculated and updated regularly. For filling the research gap, routing algorithms based on artificial intelligence techniques with an emphasis on the ant colony algorithm and the reinforcement learning of Intelligent Agents will be studied and developed to increase the computational efficiency in dealing with uncertainty and dynamic environments, such as street traffic conditions (accidents and other events). Various candidates were provided for drivers to reduce their travel costs. The Ant colony community algorithm can be used in multi-objective routing problems. Another motivation for choosing the ant algorithm is to solve the vehicle routing problem to create powerful potential answers inspired by the behaviour of ant legislation. It is similar to the behaviour of some drivers in search of the optimal path moving in the transport network. This algorithm processing speed is higher than the other routing algorithms. In order to increase the power of the proposed ant colony algorithm, the ant algorithm combined with reinforcement learning methods will be used.

The following article is divided into various sections. Section 2 includes the assumptions of the study describes model problems based on multi agent systems. In the third section, the methodology of the research is given, as well as an introduction of the ANT-Q algorithm and its features and how to implement it in connection with the investigation. Section 4 presents an algorithm including the parameter setting, calculation and analysis of the case study, is performed by the simulation. Finally, section 5 delivers the summation and conclusion of the paper.

2. Description of the Problem Based on Multi Agent Systems

Before describing how to model a problem based on multi agent systems, the main assumptions that have been considered in this study can be described as follows:

- We conduct this research in the area of urban transport network based on the node-arc model; assuming intersections as nodes and street intersections as arcs with limited capacity.
- Access to all roads in the transportation network is provided homogeneously by the drivers.
- Considering the research for private vehicle drivers' selections of multiple routes between source and destination sites.
- Solving routing or guiding problems from a source to a destination (the end of the trip during the path or intersection is not checked).
- Considering drivers' routing preferences (assuming that the routing problem is user-based).
- Route guidance during the trip and decision making for guidance before the vehicle reaches an intersection.
- Connivance of ITS equipment failure in collecting required data (regardless of traffic data collection errors).
- In this research, route guidance can only be provided for drivers who are equipped to receive messages, but not for all drivers in the network.
- Real-time travel time information presents dynamic information associated with changes in travel times in the current situation. Use of the real-time information is possible with video systems or cameras, magnetic loops, global positioning systems (GPS) and other sensors in a transportation network. Thus, the dynamic routing of vehicles that will be examined in this study requires this information.
- In order to we deal with the uncertainty of the network, the Intelligent Agents approach is used on nodes (or intersections).
- Communication and cooperation between neighbouring agents is considered in routing.

- Environmental conditions are fully understood by the agents (assuming the Markov nature of the agent learning process)
- Defining the reward function of Intelligent Agents as multi criteria and are based on travel time, speed, traffic volume and level of service.

According to the studies reviewed in the previous section about the application of agent-based systems for traffic management (especially route guidance systems), a conceptual framework to guide the vehicles based on Intelligent Agents areas is as follows:

According to the steps in the urban transport planning process, an urban transport network is divided into geographically limited areas. Then we consider each of the areas of the map that is available, as a graph (or network). When the vehicle reaches each are it is guided by network nodes with local decisions to the desired destination. In order to understand the dynamic environment conditions and to adapt to unspecified changes in network conditions (accidents, emergency repairs of streets, etc.) and for updating network nodes with traffic information (local information), we used a number of Intelligent Agents to control and define the nodes. Thus, the nodes of the network will be smart. This agent uses past experiences in addition to collecting and storing transportation data. Other features of the framework include how it considers the communication of agents or uses the communication systems. Thus, with agents, necessary calculations based on real-time traffic information to guide vehicles in the nodes are completed, and each node offers the next path to the driver. The problem description is depicted in the schematic Figure 1.

This combinatorial optimization algorithm was introduced by Colorni et al. (1991). The main basis of this algorithm is the Ant System (AS) that a group of ants (or agents), which to gather find good solutions for the optimization problem. The Ant-Q algorithm is actually a connection between reinforcement learning (particularly Q-learning) and the ant colony system. We suppose that our network is composed of links and nodes. Each node is a state and each link an action. Let k be an

ant (agent) that is tasked with routing. Associated to k, the list $J_k(r)$ of nodes still to be visited, where r is the current node (this is equivalent to say that ant k remembers already visited cities). An ant (agent) k situated in node r moves to nodes using the following rule, called *pseudo-random-proportional* action choice rule (or state the transition rule)
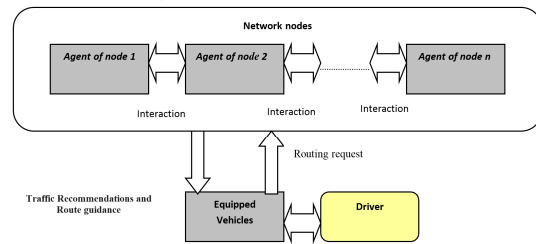
Figure 1. The ANT-Q Algorithm and Its Implementation Related to the Research Problem

$$S = \begin{cases} \arg\max_{u \in J_k(r)}\{[AQ(r,u)]^{\delta}.[HE(r,u)]^{\beta}\} & if \ q \leq q_0 \\ S & otherwise \end{cases} \quad (1)$$

Where:

- AQ(r,u), (Ant-Q-value) is a positive real value associated to arc (r,u) and is the Ant-Q algorithm counterpart of Q-learning Q-values. AQ(r,u)'s are changed at run time and are intended to indicate how useful it is in making a move to s (i.e., to go to nodes) when in state r.
- HE(r,s), is a heuristic function which evaluates the goodness of a move to s when in node r. In the ATSP (asymmetric travelling salesman problem), HE(r,s) is the inverse of the distance between cities r and s [Gambardella and Dorigo 1995], but in this paper we calculate HE(r, s) as the inverse of the reward function.
- Parameters β and δ weigh the relative importance of the learned AQ-values and the heuristic values.
- q is a value chosen randomly with uniform probability in [0, 1], and q_0 ($0 \leq q_0 \leq 1$) is a parameter: the smaller q_0 the higher the probability to make a random choice.
- S is a random variable selected according to the distribution given by formula (2), which gives the probability with which an ant in node r chooses to move to node s.

$$p_k(r,s)$$
$$= \begin{cases} \dfrac{[AQ(r,s)]^\delta . [HE(r,s)]^\beta}{\sum_{u \in J_k(r)}[AQ(r,s)]^\delta . [HE(r,s)]^\beta} & if \ s \epsilon J_k(r) \quad (2) \\ 0 & otherwise \end{cases}$$

- As we said, the goal of Ant-Q is to learn AQ-values such that they can favour, in probability, the discovery of good ATSP solutions. AQ-values are learned by the following rule (3). The parameters α, γ are learning rate and discount factor.

$$AQ(r,s) \leftarrow (1- \qquad\qquad (3)$$
$$\alpha).AQ(r,s) + \alpha.[\ \Delta AQ(r,s) + \gamma.\max_{z \in J_{K(S)}} AQ(s,z)]$$

- The update term is composed of a reinforcement term and of the discounted evaluation of the next state. In general, the reinforcement ΔAQ can be local (immediate) or global (delayed). In the current version of Ant-Q local reinforcement is always zero while global reinforcement, which is given after all the ants have finished their route, is computed by the following formula (4):

$$\Delta AQ(r,s) =$$
$$\begin{cases} \dfrac{W}{L_{k_{ib}}} & if(r,s)\epsilon \ tour \ done \ by \ agent \ k_{ib} \quad (4) \\ 0 & otherwise \end{cases}$$

K_{ib} is agents that contrast best to our current iteration. Where L_{kib} is the sum of rewards done by

the best ant (agent), that is the ant which did the minimum cost in the current iteration, and W is a parameter [Gambardella and Dorigo 1995].

Briefly, the steps for implementation ANT-Q is as follows: first, the initialization phase defines the initial value to AQ given and any agent or ant K according to some policy, placed in the initial node. The groups of nodes that must be met are classified. In the next step, each of the m agent, move and the AQ (r,s) value using a discount rate to evaluate the next state is updated until each agent complete its tour and returns to the origin node. In the third step, the length of each tour (L_k) is calculated by each agent and is used for calculating ΔAQ (r,s). The amounts of AQ (r,s) are updated based on the presented updated formulation. Finally, in the fourth step, if the termination condition is met, the algorithm will return to the second step. Usually, when the number of iterations ends or recovery does not appear after the iteration algorithm stops. According to algorithms flow diagram shown in Figure 2, the different steps of these algorithms are as follows:
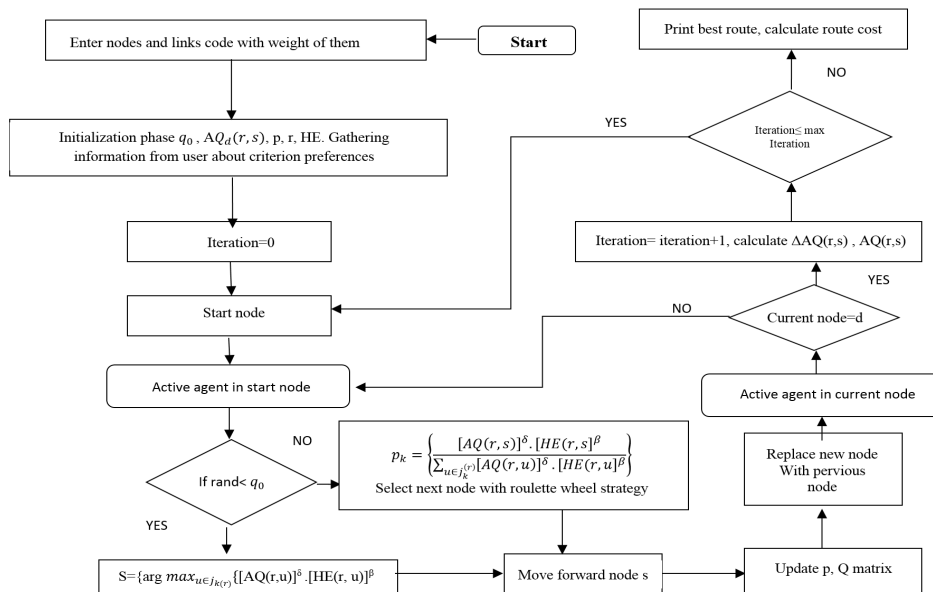

Figure 2. Flow Diagram of Proposed Algorithm

In this study, in order to consider the preferences of vehicle drivers and define the Multi Criteria reward function AQ, various characteristics are used, including travel time f_{travel}, speed f_{speed}, traffic volume f_{flow} and level of service f_{LOS}.

Before the introduction of the multi criteria reward function model, the method of dimensionless parameters based on the fuzzy dimensionless model is presented as the following relationships:

Criteria by negative aspect:

$$(f_x) = \frac{\max(f_x) - f_x}{\max(f_x) - \min(f_x)} \quad , \qquad (5)$$
$$0 \le Norm(f_x) \le 1$$

Criteria by positive aspect:

$$Norm(f_y) = \frac{f_y - \min(f_y)}{\max(f_y) - \min(f_y)}, \qquad (6)$$
$$0 \le Norm(f_y) \le 1$$

Min (f_x) and max (f_x) are the minimum and maximum values of (f_x) between different solutions or paths and between each pair of origin and destination. In the above equations with respect to the negative aspect of travel time, traffic flow and level of service (i.e., traffic volume to road capacity) used formula (5) for normalization. However, for speed, due to its positive nature, formula (6) is used for normalization. Furthermore, for easy calculation, speed can be multiplied minus the change to its nature. Therefore, formula (5) is used here for normalization. Therefore, the reward Multi Criteria function can be written as follows:

$$
AQ = \begin{array}{l} w_1 * \text{Norm}(f_{flow}) \\ +w_2 * \text{Norm}(f_{travel}) \\ +w_3 * Norm(f_{speed}) \\ +w_4 * \text{Norm}(f_{LOS}) \end{array} \qquad (7)
$$
$$w_1 + w_2 + w_3 + w_4 = 1, w_1, w_2, w_3, w_4 \ge 0$$

In the model presented above, which shows discrete multi criteria, according to formulation (7), which is based on minimizing the Simple Additive Weighting, we follow the transfer of vehicles from a origin to a destination along the shortest path in dynamic network conditions with the objective of minimizing the total cost of the trip, including travel time, speed, traffic flow and level of service. In formulation (7), w_1 is the weight of traffic flow parameters or coefficients importance of traffic flow, w_2 is the weight of the travel time parameter, w_3 is the weight of the speed parameter and w_4 is the weight of level of service. These weights are based on the suggested drivers' preferences.

4. Running the Algorithm (Case Study)

In order to study the behaviour of the proposed algorithm and understand how user-based vehicles are guided based on interaction and learning agents (or ants), part of the Tehran city transportation network, for which a traffic map is available (Figure 3), is considered as the test bed and adopted using the node-arc model (Figure 4). The studied network, consists of residential areas in the traffic plan that is limited to the north by Fatemi and Motahari Avenue, to the east by Shariati and 17th September Avenue, to the south by Shosh Avenue, and to the west by Kargar Avenue and consists of 56 arcs and 53 nodes. All information related to network that consist of speed, travel time and traffic volume, gathered by the Tehran traffic control centre through a camera mounted in this area and obtained with using the AIMSUN version 7.0 software simulator. Furthermore, the physical characteristics of the network, including the arc lengths of the network and the capacity of the arc, have been used for updating the information of GIS.

To evaluate the proposed route guidance algorithm, different traffic scenarios are considered as pairs of Origin - Destination 479 and 572. Node 479 (Imam Khomeini) is the intersection from which the vehicles began moving and node 572 (Shosh square) is used as the intersection at the end of the trip.

Route 1: Imam Khomeini-Amirkabir-Mustafa Khomeini-Mahallati-Rey-Molavi-SahebJam Shoosh

Assigned code for route 1: 479-480-490-589-576-562-736-746-727-703-686-598-546-543-539-560-572

Route2: Imam Khomeini-Amirkabir-Rey-Molavi-Saheb Jam-Shoosh

Assigned code for route 2: 479-480-490-589-648-705-733-771-764-751-734-746-727-703-686-598-546-543-539-560-572

Route3: Imam Khomeini-Amirkabir-Mustafa Khomeini-Saheb jam-Shoosh

Assigned code for route 3: 479-480-490-589-576-562-554-546-543-539-560-572

Route4: Imam Khomeini-Ekbatan-Baharestan-Mostafa Khomeini-Saheb Jam-Shoosh

Assigned code for route 4: 479-480-490-512-625-532-567-592-601-593-589-576-562-554-546-543-539-560-572

Route5: Imam Khomeini-ValiAsr-Molavi-Molavi to west-Molavi-Shahrdari-Saheb Jam-Shoosh

Assigned code for route 5: 479-435-404-344-295-233-222-218-210-213-205-204-201-192-183-267-293-353-360-375-521-526-539-560-572

Moreover, success and in order to achieve the optimal performance of the proposed algorithm depends on fine-tuning the parameters. In many applications, the parameters are adjusted through the sensitivity analysis. Thus, during the various implementations of the algorithm, different parameter values are tested to achieve the optimal value of fitness function. Therefore, with adjusted parameters $\gamma = 1$, $\delta=1$, $\beta = 2$, $\alpha = 0.5$, fixed $w = 10$, $q_0 = 0.6$ and the number of iterations equal to 500, the ANT-Q algorithm that was designed as a code in MATLAB was run.

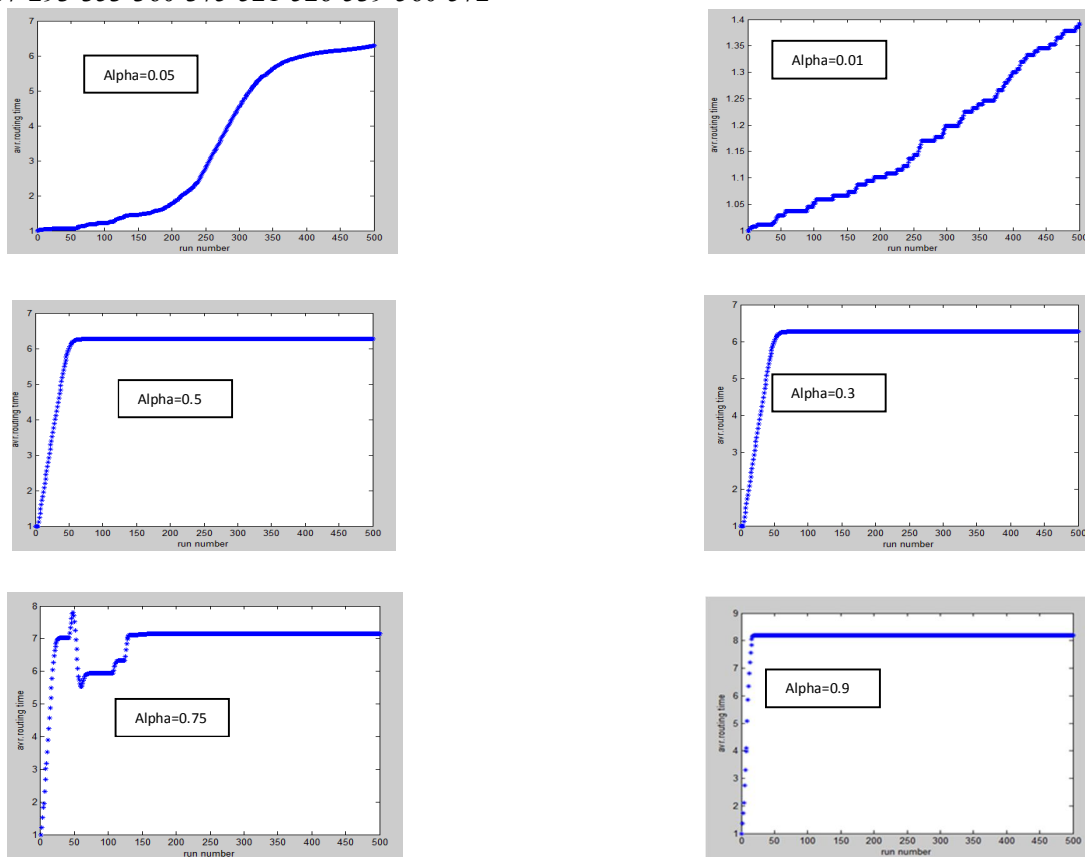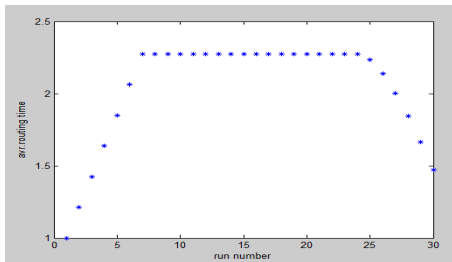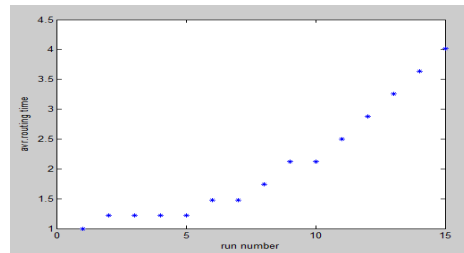The sensitivity analyses of parameters are depicted in the schematic Figure (a) and Figure (b):

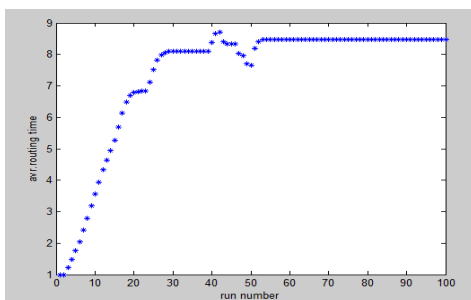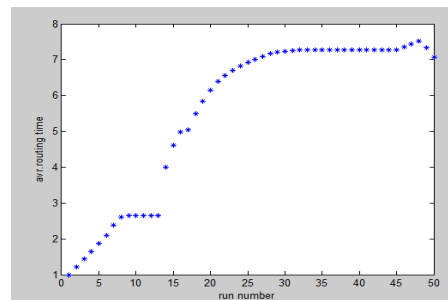**Figure (a): Sensitivity analysis of learning rate**
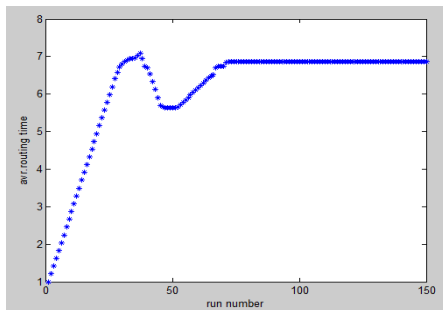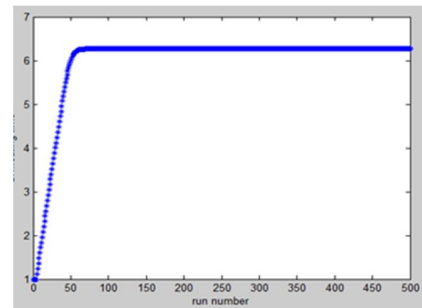
0.104033 =run time

0.054997= run time

0.147265=run time

0.262947=run time

0.349837= run time

2.459417= run time

Figure (b): Sensitivity analysis of simulation iteration
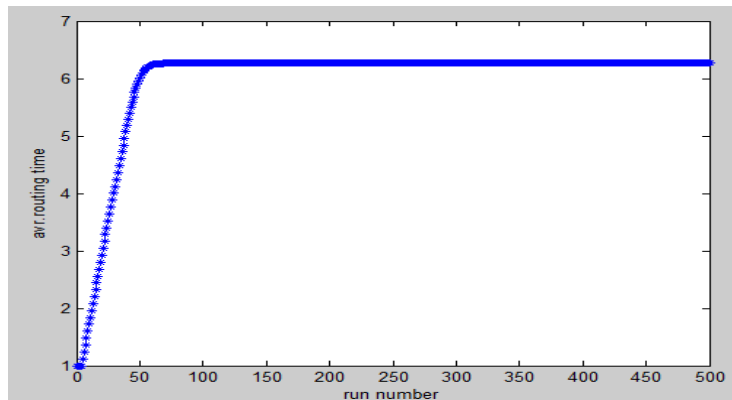**Figure 3. Sensitivity analyses of parameters are depicted in the schematic Figure (a) and Figure (b)**

Figure 4. Traffic map of part of Tehran city

Figure 5. The topology of the selected network

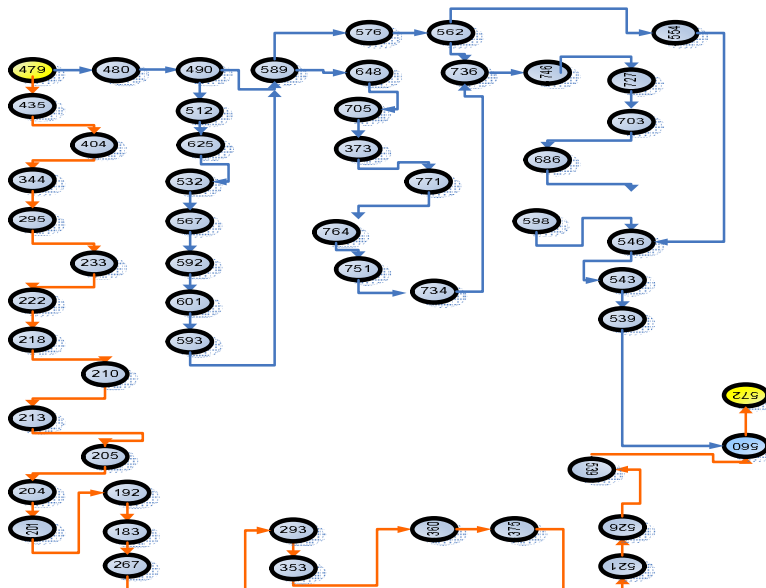**Figure 6. Graph of the convergence of the algorithm**

Figure 7. The best new solution for the considered network topology (at moment t1)
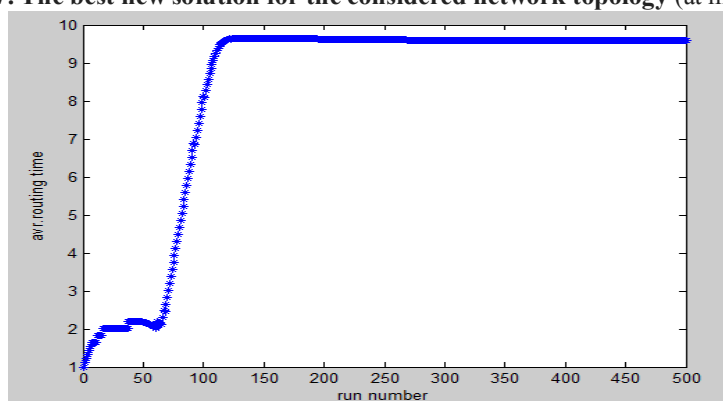

Figure 8. The trend of convergence of the proposed algorithm (arc obstruction 479-480)

The initial values of the reward function for each pair of available state - act for ants or Intelligent Agents deployed in network nodes ($m = n$) considered by the two-dimensional matrix AQ=0. In this matrix with 52 rows (nodes) and 56 columns (arcs), each row shows a separate state and each column shows a separate action. The initial values of the transition probability matrix (n is the available action) and the values of the heuristic matrix HE are calculated by the inverse of the reward function. The values of alternatives importance coefficients were calculated through questionnaires distributed among drivers using analytic hierarchy approach (AHP) and the expert choice software as follows:

$$w_1 = 0.277, w_2 = 0.203, w_3 = 0.238, w_4 = 0.281$$

Following the simulation and by using the available values in the AQ matrix, it can be seen that the route 3 has the highest value, so the 572-560-539-543-546-554-562-576-589-490-480-479 path is the lowest-cost trip. The average time of routing in each iteration of the simulation is presented in Figure 7. As can be seen in the graph, the defined criteria performance following a certain number of iterations is convergent to a constant value of approximately 6.26 (cost of unit time), indicating the completion of the learning process. Finally, we can inform the value of the simulation as a time benchmark to vehicles going in the direction of traffic on the network in an appropriate manner.

Considering the following in according to the traffic information provided (at the moment t1) about the latest state of network traffic based on arc obstruction 479-480, vehicle drivers should adapt the path to new circumstances. Thus, the proposed algorithm should calculate a path with the lowest cost from node 479 as the origin to the destination node. The best new solution is depicted in Figure 7. Furthermore, after this variation, the average times of routing in each iteration of the simulation are presented in Figure 7.

4.1 Managerial Insights
The increase in transportation demand can be met by providing additional capacity. However, this may no longer be economically attainable or feasible. Thus, the emphasis has shifted to improving the existing infrastructure without increasing the overall nominal capacity, by means of an optimal utilization of the available capacity. Two complementary measures can be taken: improving the management systems by use of recent developments in the areas of communication and information technology, and improving the management via control techniques. The set of all these measures is framed as Intelligent Transportation Systems. Artificial intelligence and multi-agent techniques have been used in many stages of these processes. Dynamic route guidance systems that are based on information and communication technologies are important in the area of Intelligent Transportation Systems activity. In this research, the routing algorithm based on artificial intelligence techniques with an emphasis on Intelligent Agents has been developed to increase the flexibility of driver decision-making in dealing with uncertainty and dynamic environments, such as traffic conditions.

5. Summary and Conclusions
In this paper, formulation of the problem of dynamic guidance in intelligent transportation systems and vehicles based on the features of the user-centred approach to incorporate socio-economic realities, and the more complete description of traffic with the purpose of satisfying users was conducted. Furthermore, due to the time varying nature of traffic networks and due to changes in traffic conditions, routes should be updated regularly, a multi agent model of routing algorithms based on artificial intelligence techniques with an emphasis on the ant colony community integrating algorithm and reinforcement learning Intelligent Agents was studied and developed. In the proposed algorithm used, a combination of the ant colony system with other techniques, namely, Reinforcement Learning (particularly Q-learning) was adopted to enhance the power of the AS algorithm. In addition to considering the interests of drivers using the Multi Criteria reward function AQ included travel time, speed, traffic volume and level of service. To illustrate the conceptual framework guiding the vehicles based on

Intelligent Agents, to identify and code the various components of the ANT-Q algorithm, calculations of guiding vehicles and find the lowest cost paths in a dynamic state of the environment (when travel time on the arcs is dependent to time) is conducted. Furthermore, this paper presents the research problem-solving through a case study simulation.

The results of the presented research demonstrate how to plan better trips, make better decisions about routing in the urban transportation network with the objective of defining the most effective strategies for selecting paths in adapting to dynamic traffic conditions. This will provide different route options for vehicle drivers with the aim of reducing their travel costs and more effective use of existing capacities. Future research can be done on some subjects, such as comparing results with other meta heuristic algorithms combined with reinforcement learning, designing the solution to the problem algorithm with regard to driver behaviour models in algorithms, incorporating this research together with the urban bus system in common personal vehicles routes and studying payment systems of the guiding mechanism system.

6. References

- Adler, J. L. and Blue, V. J. (1998) "Toward the design of intelligent traveler information systems", Transportation Research Part C, Vol.6, No.3, pp.157-172.

- Adler J. L. and Blue, V. J. (2002) "A cooperative multi-agent transportation management and route guidance system", Transportation Research, Part C, Vol.10, No.5-6, pp.433-454.

- Cai, C. Q. and Yang, Z. S. (2007) "Study on urban traffic management based on multi-agent system", Proceedings of the Sixth International Conference on Machine Learning and Cybernetics, Hong Kong, pp.25-29.

- Cao, Z., Guo, H., Zhang J., Fastenrath, U. (2016) "Multi agent-based route guidance for increasing the chance of arrival on time", Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence, pp.3814-3820.

- Chabrol, M., Sarramia, D. and Tchernev, N.(2006) "Urban traffic systems modeling methodology", Int. J. Production Economics, Vol.99, No.1-2, pp.156-176.

- Che, K., Li, L.-L., Niu, X.-T. and Xing, S.-T. (2009) "Research of software development methodology based on self-adaptive multi-agent systems", IEEE International Symposium on IT in Medicine & Education (ITME 2009), Vol. 1, pp. 235–240.

- Chen, B. and Cheng, H. H. (2010) "A Review of the applications of agent technology in traffic and transportation systems", IEEE Transactions on Intelligent Transportation Systems, Vol.11, No.2, pp. 485-497.

- Claes, R., Holvoet, T. and Weyns, D. (2011) "A decentralized approach for anticipatory vehicle routing using delegate multi agent systems", IEEE Transactions on Intelligent Transportation Systems, 10.1109/TITS.2011.2105867.

- Colorni A., Dorigo M. and Maniezzo V. (1991) "Distributed optimization by ant colonies", Proceedings of ECAL91 - European Conference on Artificial Life, Paris, France, F. Varela and P. Bourgine (Eds.), Elsevier Publishing, pp.134–142.

- Deflorio, F. P. (2003) "Evaluation of a reactive dynamic route guidance strategy", Transportation Research Part C, Vol.11, No.5, pp.375-388.

- Dong, W. (2011) "An overview of in-vehicle route guidance", Proceedings of the Australasian Transport Research Forum, Adelaide, Australia.

- Fu, L. (2001) "Adaptive routing algorithm for in-vehicle route guidance systems with real-time information", Transportation Research Part B: Methodological, Vol. 35, No. 8, pp. 749-765.

- Fu, L P., Sun, D. and Rillet, L. R. (2006) "Heuristic shortest path algorithms for transportation applications: State of the art", Computers and Operations Research, Vol.33, No.11, pp.3324-3343.

- Gambardella L. and M. Dorigo. (1995) "Ant-Q: A reinforcement learning approach to the traveling salesman problem", Proceedings of ML-95, Twelfth International Conference on Machine Learning, Tahoe City, CA, A. Prieditis and S. Russell (Eds.), Morgan Kaufmann, pp.252–260.

- Gu, J., Lin, E., Liu, Y. and Zhang, N. (2010) "Study on improved ant colony algorithm in dynamic multi-paths route guidance system", Applied Mechanics and Materials, Vol. 20-23, pp.243-248.

- Jiong, S. and Zhao, J. (2011) "Q-learning based multi-intersection traffic signal control model", International Conference on System Science, Engineering Design and Manufacturing Informatization, Guiyang, China, pp. 280-283.

- Karimi, A., Hegyi, A. De Schutter, B. Hellendoorn, J. and Middelham, F. (2004) "Integrated model predictive control of dynamic route guidance information systems and ramp metering," Intelligent Transportation Systems, pp. 491- 496.

- Lee, D. C (2006) "Proof of a modified Dijkstra's algorithm for computing shortest bundle delay in networks with deterministically time-varying links", IEEE Communications Letters, Vol.10, No.10, pp.734-736.

- Levinson, D. (2003) "The value of advanced traveler information systems for route choice", Transportation Research Part C, Vol.11, No.1, pp.75-87.

- Marti, I., Tomas, V.R., Saez, A. and Martinez, J. J. (2009) "A rule-based multi-agent system for road traffic management", International Joint Conference on Web Intelligence and Intelligent Agent Technology, Vol. 3.

- Masoomi, Z., Sadeghi Nearki, A. and Mesgari, A. (2011) "Designing and using a multi-objective route planning algorithm in Intelligent Transportation Systems" (In Persian), Journal of Transportation Research, Vol.8, No.1, pp.47-62.

- Nadi, S. and Delavar, M. R. (2011) "Multi-criteria, personalized route planning using quantifier-guided ordered weighted averaging operators", International Journal of Applied Earth Observation and Geoinformation, Vol.13, pp.322–335.

- Nadi, S. and Delavar, M. R. (2010) "Location-based services for in-vehicle route guidance with real time traffic information", The 12th World Conference on Transport Research.

- Ng, K. M., Ibne Reaz, M. B., Mohd Ali, M.A. and Chang, T. G. (2013) "A brief survey on advances of control and intelligent systems methods for traffic-responsive control of urban networks", Technical Gazette, Vol. 20, No.3, pp. 555-562.

- Nakhai Kamalabadi I. and Eydi, A. (2009) "Vehicle routing in dynamic route guidance system"(In Persian), Journal of Transportation Research, Vol.6, No.3, pp.269-286.
- Pahlavani P., Samadzadegan, F. and Delavar, M. (2006) "A GIS-Based Approach for Urban Multi-criteria Quasi Optimized Route Guidance by Considering Unspecified Site Satisfaction", Geographic Information Science , Lecture Notes in Computer Science Volume 4197, pp 287-303.

- Pahlavani P. and Delavar, M. (2014) "Multi-criteria route planning based on a driver's preferences in multi-criteria route selection", Transportation Research Part C 40, pp.14–35.

- Papageorgiou, M., Diakaki, C., Dinopoulou, V. , Kotsialos, A. and Wang, Y.(2003) "Review of road traffic control strategies", Proceedings of the IEEE, Vol. 91, No. 12, pp. 2043-2067.

- Park D., Laurence, R. and Choi, C. (2007a) "A class of multi criteria shortest path problems for real-time in-vehicle routing, Canadian journal of civil engineering, Vol.34, No.9, p.1096.

- Park, K., Bell, M. Kaparias, I. and Bogenberger, K. (2007b) "Learning user preferences of route choice behaviour for adaptive route guidance", Special Issue: Selected papers from the 13th World Congress on Intelligent Transport Systems and Services, IET Intell. Transp. Syst., Vol.1, No.2, pp. 159–166.

- Sadek, A. and Chowdhury, M. A. (2003) "Fundamentals of intelligent transportation systems planning", Boston, Artech House.

Sadeghi Niaraki, A. and Kim, K. (2009) "Ontology based personalized route planning system using a multi-criteria decision making approach", Expert Syst. Appl., Vol.36, pp.2250–2259.

- Schmitt, E. J. and Jula, H. (2006) "Vehicle route guidance systems: classification and comparison", Proceedings of the IEEE Intelligent Transportation Systems conference, Toronto, Canada. pp. 242 –247.

- Shi, A., Na, C. and Chun-bin, H. (2008) "Simulation and analysis of route guidance strategy based on a multi-agent game approach", 15th International conference on Management science & Engineering, Long Beach, USA, pp.140-146.

- Vandebon, U. and Upadhyay, P. K. (1997) "Simulation modeling of route guidance concept", Transportation Research Record, 1573, pp.44-51.

- Wu, J. J., Sun, H. J. and Gao, Z. Y. (2008) "Dynamic urban traffic flow behavior on scale-free networks", Physica A: Statistical Mechanics and its Applications 387, pp.653-660.

- Wunderlich, K.E., Kaufman, D. E. and Smith, R. L. (2000) "Link travel time prediction for decentralized route guidance architectures," Intelligent Transportation Systems, Vol. 1, No. 1, pp. 4-14.

- Yamashita, T., Izumi, K. and Kurumatani, K. (2004) "Car navigation with route information sharing for improvement of traffic efficiency," Intelligent Transportation Systems, pp. 465- 470.

- Yoshikawa, M. and Otani, K. (2010) "Ant colony optimization routing algorithm with tabu search", Proceeding of International Multi conference of Engineers and Computer Scientists Hong Kong: IMECS, pp. 2104-2107.

- Zolfpour, M., Selamat, A., MohdHashim, S. and Selamat, M. (2011) "Route guidance system based on self-adaptive multiagent algorithm", Computational Collective Intelligence. Technologies and Applications, Lecture Notes in Computer Science Volume 6923, pp. 90-99.