AUT JOURNAL OF CIVIL ENGINEERING

AUT Journal of Civil Engineering

AUT J. Civil Eng., 6(1) (2022) 51-62
DOI: 10.22060/ajce.2022.20125.5760

An Agent-Based Simulation for Destination Choice of Discretionary Tours: Evidence from Qazvin, Iran

I. Farzin, M. Abbasi, A. R. Mamdoohi*

Faculty of Civil and Environmental Engineering, Tarbiat Modares University, Tehran, Iran.

ABSTRACT: Spatial analysis and distribution are of great importance to transportation planners, especially in traffic demand management. Simulation is an important tool in the planning and management of transportation systems to achieve an estimation of real system behavior to evaluate different scenarios. Regarding the aggregate nature and inability to consider heterogeneity among the individuals in a large number of discrete choice models and the high cost of data collection through questionnaires, using a disaggregate and heterogeneous agent approach can be used to evaluate different policies. Since each agent is inherently autonomous and interacts with different agents and the environment to achieve its goals, this paper aims to use the agent-based approach to simulate the destination choice of discretionary tours of Qazvin citizens. Individual socioeconomic characteristics and travel information questionnaires (revealed preference) of 9938 households and 29840 individuals in 12 municipality districts of Qazvin were collected. After extracting 12 types of activity patterns including shopping and recreation trips, the simulation of destination choice in MATLAB has been studied using the Reinforcement Learning algorithm (RL) and reward-punishment functions which are based on the relative attractiveness of districts for various modes and travel times. High correlation (above 0.9) results were achieved among simulated trip destination choice distributions and observed survey data using the RL algorithm which illustrates the algorithm's goodness of fit; also the simulation results and survey data have a similar trend among districts which illustrates that the simulation findings have real-world implications.

Review History:

Received: Jun. 05, 2021
Revised: May, 13, 2022
Accepted: Jun. 18, 2022
Available Online: Jun. 29, 2022

Keywords:

Agent-based modeling
Reinforcement learning algorithm
Destination choice
Discretionary Tours

1- Introduction

Spatial analysis and distribution help to find practical solutions to reduce congestion in central business districts (CBDs) of metropolises. One of the main reasons for the congestion in urban centers is the high rate of travel demand and generation of activities [1, 2]. The spatial characteristics of the activity-travel patterns determine how the transportation system operates, which will help to determine the location of the bottlenecks in the network [3]. Transport planners identify the problems in the network and propose some solutions using travel demand forecasting to enhance the network performance. Travel demand models are considered as applied tools for decision-making in transportation system development. Travel demand forecasting has four phases of trip generation, trip distribution, modal split, and trip assignment which are called transportation four-step classic models [4]. Destination choice, mode choice, and route choice are analyzed in trip distribution, modal split, and trip assignment phases, respectively. Among these choices, destination choice is an essential part of travel demand analysis. Regarding the aggregate nature and inability to consider the heterogeneity and taste variation among the individuals in a large number of discrete choice models and the high cost of data collection through questionnaires (whether Revealed preference or Stated preference), disaggregate and heterogeneous agent approaches can be used to evaluate different policies. In an agent-based approach, each agent interacts with the environment and other agents autonomously to meet their specified goals. Agents are intelligent and act based on their knowledge, experience, and the interaction between agents related to social interactions [5].

Due to the more complex nature of discretionary trips compared with mandatory trips, this paper aims to simulate the destination choice of discretionary tours of Qazvin citizens using the Reinforcement Learning (RL) algorithm and finally, compare the simulation results with real-world survey data to evaluate the algorithm accuracy and efficiency. Considering the level of survey data that has been collected at the individual level and the features expressed in the agent-based simulation approach, this paper uses this method to simulate Qazvin citizen tours.

RL is mainly used for route choice [6-9] and departure time [6, 10-12] modeling. Few studies have used this technique in destination choice. Alvarez and Birds used agent-based

*Corresponding author's email: armamdoohi@modares.ac.ir

Fig. 1. Agent and environment interaction in RL algorithm [21].

modeling to evaluate the destination choice of tourists. Their model assumed that destination choice depends on tourists' tastes (characterized by their preferences for goods and services) and their socioeconomic characteristics [13]. Vitins and Erath used new kinds of destination choice models to account for information on individuals and used agent-based modeling advantages [14]. Bazzan and Grunitzki used a multi-agent reinforcement learning approach to en-route trip building. In their paper, individual drivers are considered as active and autonomous agents, which, instead of having a central entity assigning complete trips to each agent, build these trips by experimentation during the actual trip. Their results were compared to iterative, centralized methods and concluded that an agent-based perspective yields choices that are more aligned with the real-world situation because (i) trips are computed by the agent itself (and not provided to the agent by any central entity), and (ii) it is not based on pre-computed paths (rather, it is built during the trip itself) [15]. Yang *et al.* use an interactive RL algorithm to simulate the time and location characteristics of people's activities. They used four reward-punishment functions including region attractiveness index, activity duration, activity start time, and travel time. To investigate the effects of agents' decisions on each other, road congestion degree has been added to the algorithm [16]. Ding *et al.* simulate destination choice of shopping and recreation trips of Tongling, China citizens. Each agent has 27 traffic zones as a destination choice. RL and Q-learning algorithms are used for providing agent learning. In their study, the environmental rewards for each state and action are defined based on the travel time, the number and floor space of locations at the destination to perform the activity [3]. One of the limitations of this study was that they did not consider punishment function in their simulation process. Janssen *et al.* modified an RL algorithm using a regression tree to simulate the sequence, start and end time of each agent's activities within a week. The regression tree or Q tree generalizes triples (state, action, and Q value) based on the examples obtained during the learning process. They defined two components of activity choice and activity duration for each agent state and used the trip information of 2,500 households in Flanders, Belgium [17].

According to the aforementioned studies, the main contributions of this study are: 1) Most of the previous studies were conducted in developed countries but we aimed to calibrate a destination choice of discretionary tours using the RL algorithm in Qazvin, Iran as a developing country; 2) we have considered reward-punishment as the function of regions' attractiveness and travel time, respectively; 3) Most reinforcement learning studies are based on many assumptions and lack support from survey data, making the results difficult to apply in practice. According to previous studies, the research hypotheses are: 1) the proposed model would significantly explain the variation in destination choice of discretionary trips (H1); 2) agents are more likely to choose destinations with higher attractiveness in their shopping and recreation trips (H2).

This paper is structured as follows: Section 2 is concerned with RL algorithm methodology. Section 3 introduces the data, and section 4 presents data analysis and simulation results. Finally, Section 5 outlines the major conclusions and suggestions for future studies.

2- Methodology

RL is the process of determining what to do and how to map conditions to behaviors to maximize a numerical reward signal [18, 19]. Unlike most ways of machine learning, the learner is not told which actions to take; however, the learner must determine which actions yield the most reward by undertaking them. In the most complex situations, actions will influence not just the immediate reward, but also the next situation and, by extension all subsequent rewards [20].

RL deals with problems in which an autonomous agent understands states and accordingly perceives, and performs optimal actions to achieve his/her predetermined goals. Whenever an agent acts as the environment, he/she received a punishment or reward according to the state and action performed. For example, an agent may receive a reward for a win or punishment for a loss and no rewards for others. The task of an agent is to learn these rewards and tries to get the most cumulative reward function in the next actions. Through an RL problem, the agent communicates with the environment by trial and error, learning to choose the optimal action to accomplish his or her goal [21] (Fig. 1). This approach has been taken into consideration because of the training of agents through the rewards and penalties and without specifying how to act.

The task of an agent is learning a policy such as $\pi : S \rightarrow A$ (S: state, A: action) which could select the next step according to the current state (S_t). One of the proper solutions to determine the optimal policy is to define it in a manner that maximizes the cumulative reward function over time. Eq. (1) illustrates the cumulative reward function received from the policy π of starting state (S_t) [22].

$$V^{\pi}(S_t) = r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + ... = \sum_{i=0}^{\infty} \gamma r^{i}{}_{t+i} \tag{1}$$

where r_{t+i} is the rewards that receive from the policy π of starting state (S_t). γ is a constant for delayed rewards which range [0, 1). In general, the effect of the reward given i step after the action is reduced by the power factor γ^i.

Optimal policy (π^*) learning in a preferred environment is not possible through direct learning because there are no training examples in form (s, a) and only reward values $r(s_i.a_i)$ are available. The Q-learning algorithm is one tool for determining the optimal policy. In Q-learning, the researcher should find a reliable way to estimate training values for Q through available data (series of r rewards over time). This can be achieved by iterative estimation [23].

In this algorithm, the learner considers the $\hat{Q}$ matrix with a large table for each state and action pair. In the first step, the table is filled with random values. Next, the agent observes the state of s and acts such as a, then receives *r*=*r*(s, a) as a reward and $s' = \delta(s,a)$ as the final state. In the next step, the agent updates $\hat{Q}$ (s, a) value for the current state according to Eq. (2):

$$Q(s,a) \leftarrow r + \gamma \max Q(s',a') \tag{2}$$

This cycle continues until it reaches a steady state and minor changes occur in the *Q* matrix in successive iterations.

To execute the Q-learning algorithm, reward and punishment functions are considered as zone attraction for the selected mode and travel time which are defined as follows:

Reward based on the degree of attractiveness of districts by specific mode: in this paper, the location of the activity is considered as municipality districts of Qazvin which contained different land uses. Some people prefer to travel to locations with more attractive land-use characteristics, despite the long distance from the origin. To quantify, the reward is based on the district's attractiveness. Unlike previous studies that rewarded function was only dependent on the type and location of activities, this paper considered the travel mode of the activity, too. In other words, the degree of attractiveness of a district for a specified activity depends on the number of activities carried out by a specified travel mode and is calculated for 12 municipality districts as Eq. (3):

$$attract_{ij}^{m} = \frac{n_{i,j}^{m} - n_{i,\min}^{m}}{n_{i,\max}^{m} - n_{i,\min}^{m}} \tag{3}$$

where $attract_{ij}^{m}$ is the attraction of zone j for people residing in zone i using mode m for shopping or recreation activities; $n_{i,j}^{m}$ is the number of activities for the shopping or recreation of residents of zone i in zone j and using mode m; $n_{i,\min}^{m}$ is the minimum number of activities for shopping or recreation of residents of zone i in 12 municipality traffic zones utilizing mode m; $n_{i,\max}^{m}$ is the maximum number of activities for shopping or recreation of residents of zone i in 12 municipality traffic zones using mode m .m is the chosen mode for shopping or recreation activities (including walking, cars, and bus).

To use a unique scale for reward and punishment functions, the reward calculated by Eq. (3) multiplied by 20 (Eq. (4)):

$$reward = 20 * attract_{ij}^{m} \tag{4}$$

Punishment function based on travel time: Considering punishment as travel time prevents overly attractive districts from being selected. In this paper, only three modes of walking, car, and bus are intended for shopping or recreation activities, and the travel time of modes between different destinations is taken into account. Also, to consider the penalties for travel time, the proposed relationship by [17] is used as Eq. (5):

$$Punish(t) = -c * (b * t)^{a} \tag{5}$$

where Punish (*t*) is the punishment according to the travel time; *t* is the travel time, and *a*, *b*, and *c* are the proposed coefficients by [17] (Table 1).

The algorithm shown in Fig. 2 is used to simulate the shopping and recreation tour destination choice. In this algorithm, agents are placed in one of the groups based on their activity pattern. For the convergence criterion, one of the following situations should be reached: 1) No action is possible for the agent in the current situation; 2) The *Q* function in step (i+1) is not much different from the value in step (i) (convergence criterion of *Q* function value is 0.0001); 3) For a specific situation, all actions are checked. Also, in the trial and error phase, each agent searches for a possible action depending on the current situation randomly. The agent tries to optimize the *Q* function with different trials and errors.

This algorithm is summarized into the following three steps:

Step 1: Use Qazvin citizen trips census data to derive activity patterns, Agent classification based on their

Table 1. proposed coefficients by Janssens et al. to calculate travel time penalties for different modes [17].

Coefficient \ Mode	Walking	Car	Bus
a	1.6	0.6	0.8
b	1/12	1/6	1/6
c	5	5	5

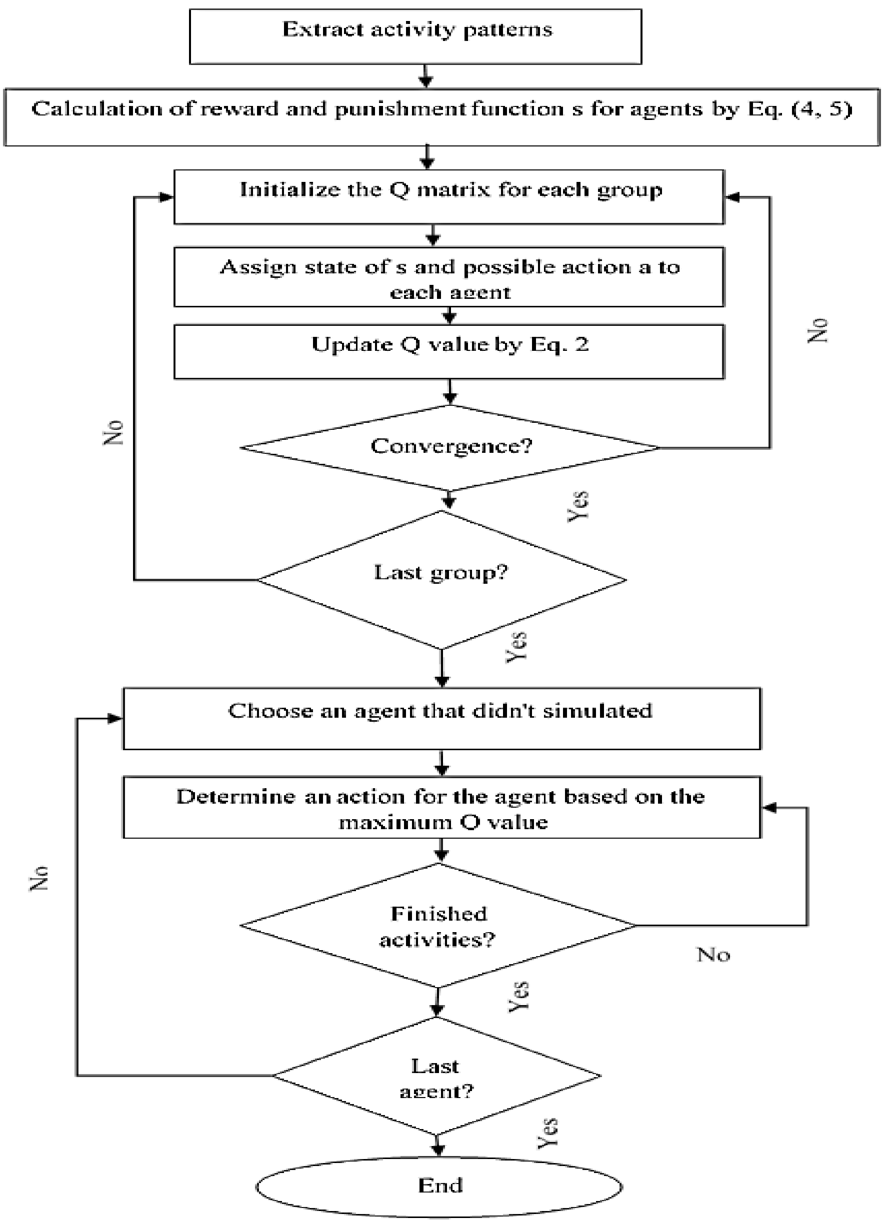

Fig. 2. Proposed algorithm for simulating destination choice of shopping and recreation trips.

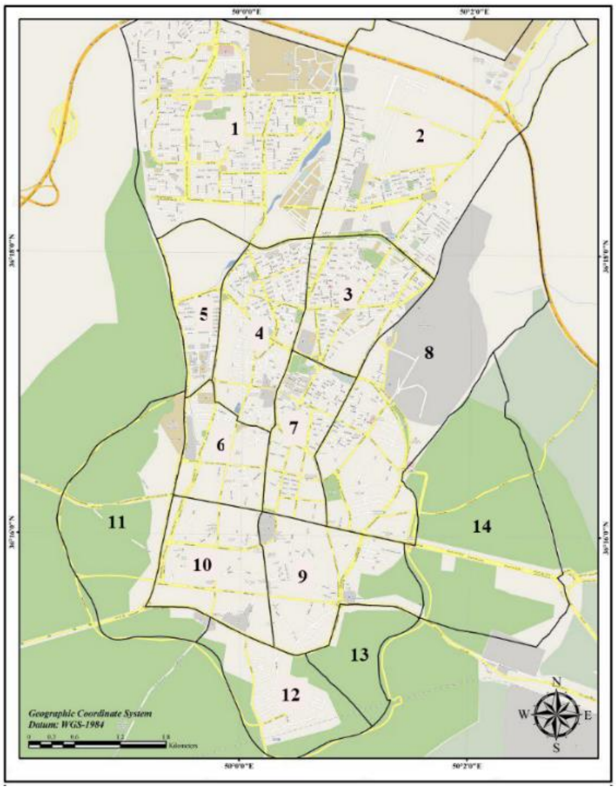

Fig. 3. Municipality districts in Qazvin city [24].

activity pattern, and use census data to calculate reward and punishment functions.

Step 2: Estimating the value of the Q function by trial and error until the convergence of the Q matrix and

Step 3: Simulate the destination choice of shopping and recreation tours using the calculated Q value in the previous step.

3- Data

To simulate the destination choice of shopping and recreation tours, the city of Qazvin with a population of about 403,000 has been selected as a case study (Fig. 3). Qazvin is located in the northern half of Qazvin province in Iran. The data used in this research was obtained from an extensive travel survey of Qazvin citizens during the Qazvin urban transportation master plan (QUTMP). The survey includes individual socioeconomic characteristics and travel information. Travel information consist of departure and arrival times, origin, destination, travel mode, and trip purpose. The questionnaires in the QUTMP study were designed using the revealed preference (RP) method and asking for the actual choice of passengers in real conditions [24]. Revealed preference surveys (RP) are about choices that individuals have actually made [25]. In the Qazvin Urban Transportation Master Plan study, travel information was collected from 9938 households and 29840 individuals in 12 municipality districts which contain 10 trip purposes.

Table 2 shows a frequency analysis of people's trip purposes, accordingly shopping and recreation trip relative frequencies are 7.7 and 3.6 %, respectively. Among different trip purposes, returning to home accounts for almost 50% of trips and medicinal trips have the lowest share (1%).

In the next step, Qazvin citizen tours were extracted and 640 tour patterns were obtained. Since the purpose of this study was to simulate destination choice of shopping and recreation trips using modes such as walking, car, and bus (due to the availability of travel time information with these modes), the information refinement was carried out in the following manner:

Shopping and recreation trips by other modes were excluded.

Trips that were intended for shopping or recreation out of Qazvin were excluded from the database.

To reduce the random error, only the travel pattern with a frequency of more than 10 was used.

Finally, 12 patterns of activities according to Table 3 were extracted. Among different activity patterns, going shopping from home and returning to home (HSH) account for 62% of the patterns.

The socioeconomic characteristic of the sample has been

Table 2. Frequency analysis of Qazvin citizen trips by trip purpose.

No.	Trip purpose	Frequency	Relative frequency (%)
1	Work	4522	15.2
2	Educational	4904	16.4
3	Shopping	2297	7.7
4	Visit offices	574	1.9
5	Visit relatives (acquaintances)	1252	4.2
6	Recreation	914	3.6
7	Drive somebody/something	513	1.7
8	Return home	14405	48.3
9	Medicinal	298	1.0
10	Others	161	0.5
	Sum	29840	100.0

Table 3.Patterns of tours used to simulate destination choice of discretionary trips of Qazvin citizens.

No.	Tour patterns	Frequency
1	Home → Shopping → Home	856
2	Home → Recreation → Home	282
3	Home → Educational → Home → Recreation → Home	56
4	Home → Work → Home → Shopping → Home	34
5	Home → Educational → Home → Shopping → Home	49
6	Home → Shopping → Home → Visit acquaintances → Home	31
7	Home → Work → Home → Recreation → Home	12
8	Home → Work → Home → Educational → Home	13
9	Home → Shopping → Home → Work → Home	10
10	Home → Shopping → Home → Recreation → Home	10
11	Home → Shopping → Home → Shopping → Home	13
12	Home → Visit offices → Home → Shopping → Home	14
	Sum	1380

Table 4. Frequency analysis of citizens' socioeconomic characteristics.

	Variables	Frequency	Percent
Gender	Female	6089	42.3
	Male	8320	57.7
Age	14 ≤	2048	14.2
	15-24	3449	23.9
	25-44	5776	40.1
	45-64	2705	18.8
	65 ≥	431	3.0
Education	High school or lower	7952	55.2
	Diploma degree	3295	22.9
	Bachelor of Science (B.Sc.)	2617	18.1
	Master of Science (M.Sc.)	433	3.0
	Ph.D.	112	0.8
Household size	1	126	0.9
	2	738	5.1
	3	2942	20.4
	4	6574	45.6
	5	3031	21.1
	6+	998	6.9
Occupation	Employee	1695	11.8
	Student	5248	36.4
	Housewife	2957	20.5
	Teacher	576	4.0
	Labour	1308	9.1
	Retired	512	3.6
	Other	2113	14.6
Car ownership	0	4968	34.5
	1	8569	59.5
	2	770	5.3
	3+	102	0.7

presented in Table 4. Male accounts for 58% of the examined sample. Moreover, the majority of respondents aged between 15 and 44 accounted for 64% with high school or lower education level. Among different households, 4-person households have the majority share in the sample, accounting for 45% of respondents.

4- Simulation results

After running the simulation model in MATLAB software, the coefficient of determination is used to evaluate the efficiency and accuracy of the proposed algorithm as in previous studies [1, 15]. In shopping activities, the coefficient of determination is 0.933, which means that 93.3% of the variation in real-world data (number of activities in districts based on the algorithm and the survey data) is explained by the simulation model (Fig. 4). In addition, the correlation between simulated data and real-world data is 0.965 which indicates a strong, direct relationship. T-test used for checking the significance of estimated coefficients. The T-score value of the simulation model (38.24) indicates that the estimated coefficient is significant at a 99% confidence level. In the case of recreational tours, the coefficient of determination is 0.991, which means that 99.1% of the variation in real-world data (number of activities in districts based on the algorithm

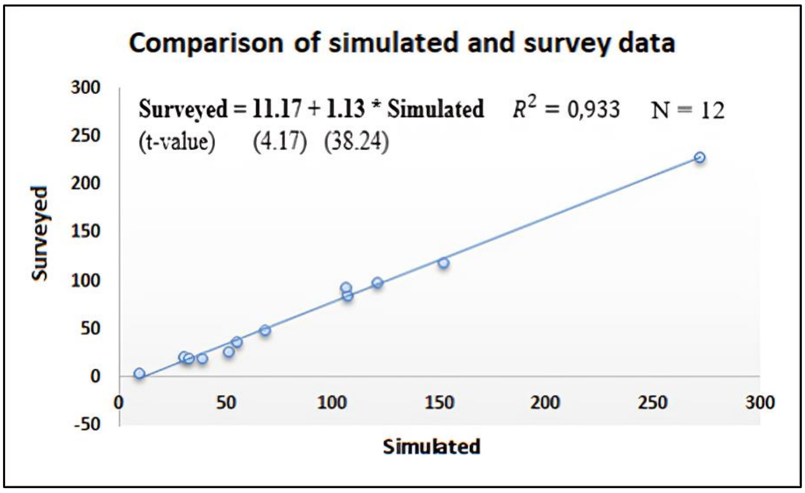

Fig. 4. Predicted-Observed scattergram for shopping tours.

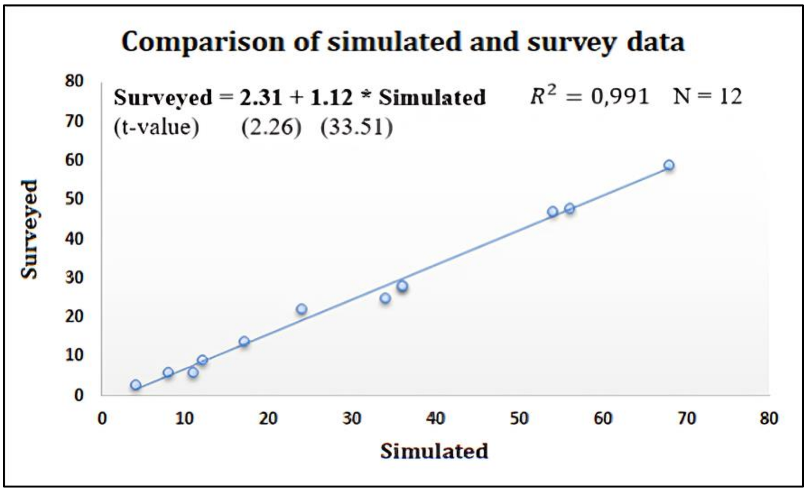

Fig. 5. Predicted-Observed scattergram for recreation tours.

and the survey data) is explained by the simulation model (Fig. 5). In addition, the correlation between simulated data and real-world data is 0.995 which indicates a strong, direct relationship. The T-score value of the simulation model (33.51) indicates that the estimated coefficient is significant at a 9 % confidence level. Considering the goodness of fit indices, we can conclude that the proposed model has a good performance and H1 accepted at least a 95% confidence level. Regarding the values of coefficient of determination, correlation coefficient, and t-score, we can conclude that the proposed simulation model can be used both as an analysis tool for predicting the effect of changes to existing systems and as a design tool to predict the performance of new systems under varying sets of circumstance.

To represent the situation in Qazvin, the findings are extended in accordance with the sampling proportion of each district. Figs. 5 and 6 show the simulation results of all agents' choices for daily shopping and recreation locations. According to both the figures, the simulation result and survey data have a similar trend which is in line with previous studies [3, 15]. As for destination choices for shopping (Fig. 6) and recreation (Fig. 7), municipality districts 1, 4, and 10 are more attractive because of their land use characteristics. In other words, there are many destinations for recreation and shopping purposes. For example, many parks, gyms, restaurants, coffee shops, and cinemas in districts 10, 4, and 1. These places are also

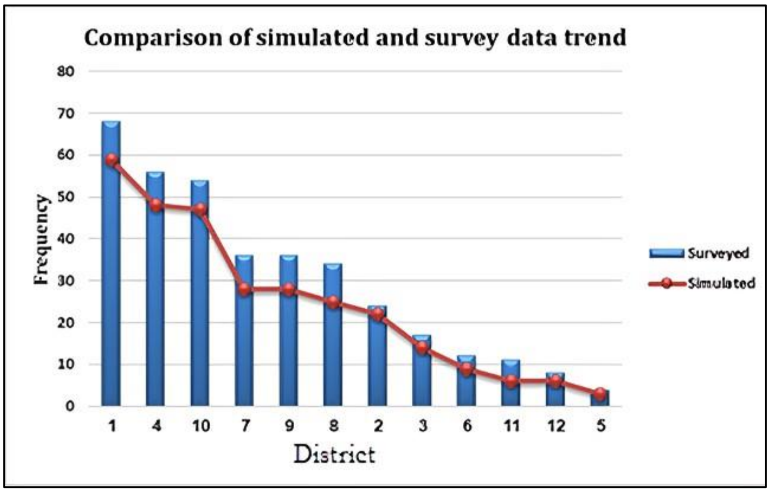

Fig. 6. Frequency of choosing districts for shopping trips in the simulation model and real data.

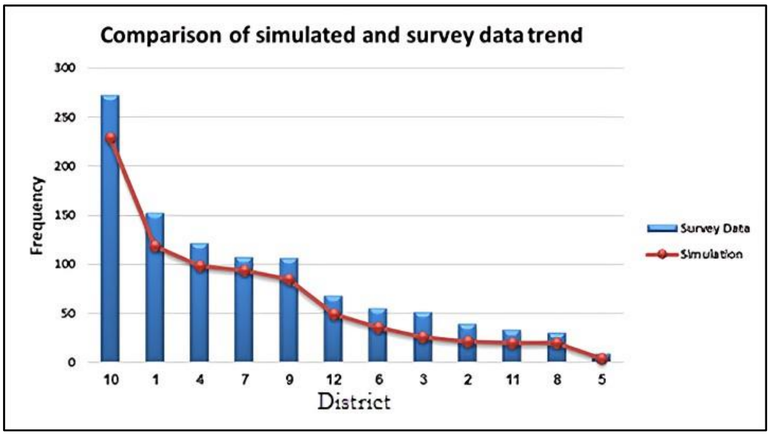

Fig. 7. Frequency of choosing districts for recreation trips in the simulation model and real data.

located in other districts but according to previous studies, people are more likely to go to recreational places which are more affordable, have more facilities, and have parking for cars [3, 13]. In the case of shopping trips, many factors affect the destination choice for these trips such as accessibility, parking spaces, number of shopping centers, attractiveness, and other related ones. Considering the land use of districts 1, 4, and 10, these destinations were so interesting for travelers' shopping trips. As can be seen, the district of 5 is the least attractive destination for shopping and recreational trips because it has been located on the west of Qazvin (Fig. 2) and it is a less developed district which is in accordance with previous studies [3, 15]. As an implication for policy and practice, it is recommended to establish more discretionary facilities for shopping and recreation activities such as the park, gym, shopping center, etc. in this district.

Moreover, it can be seen that districts 1, 4, and 10 accounts for 50% of shopping and recreational tours (Fig. 8). Hence, most of the travelers (50%) choose these districts more frequently. From the land use view, it can be concluded that diversity or mixed land use does not exist and people from other districts have to go to other districts for their shopping and recreational trips. In this regard, as an implication for policy and practice, we can recommend enhancing the mixed land use in Qazvin's districts to reduce inter-district trips which is in line with previous studies [7, 13]. According to

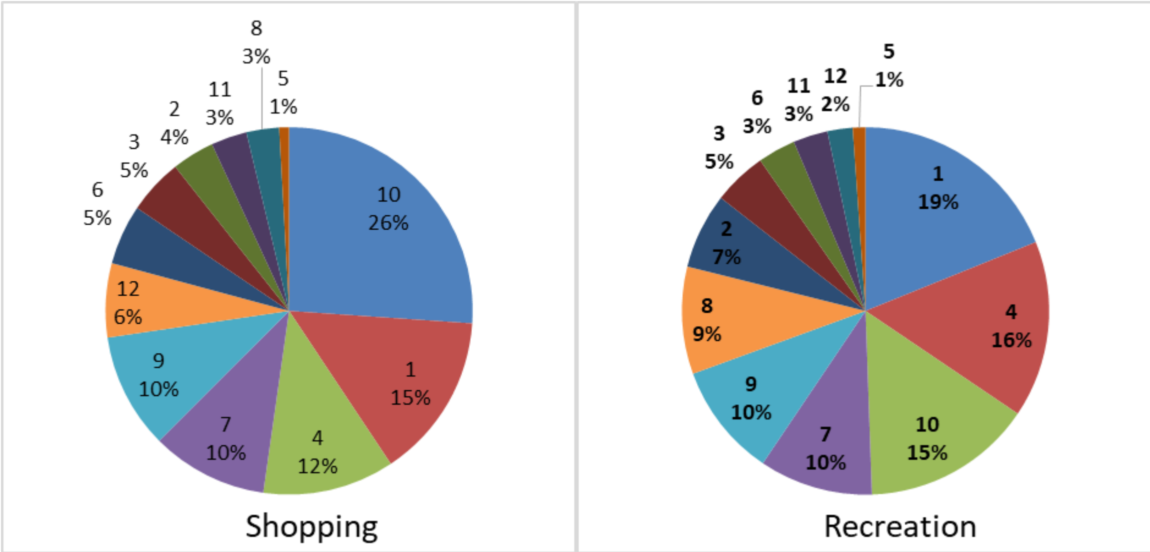

Fig. 8. Relative frequency of shopping and recreation trip destinations.

the findings, H2 is also accepted at a 95% confidence level.

Given one of the advantages of the RL algorithm, there is no need for a specific system to exist. As another implication, it can be mentioned that according to the proposed punishment-reward functions, this algorithm can be used in areas that were in the early stages of design, or if changes are made in the existing network.

5- Conclusion

Spatial analysis and distribution help to find practical solutions to reduce congestion in central business districts (CBDs) of metropolises. One of the main reasons for the congestion in urban centers is the source of travel demand and the generation of activities. The spatial characteristics of the activity-travel patterns determine how the transportation system operates, which will help to determine the location of the bottlenecks in the network. To conduct spatial analysis, simulation is an important tool in the planning and management of transportation systems to achieve an estimation of real system behavior to evaluate different scenarios Regarding the aggregate nature and inability to consider the heterogeneity among individuals in a large number of discrete choice models and the high cost of data collection through a questionnaire (whether Revealed preference or Stated preference), using a disaggregate and heterogeneous agent approach can be used to evaluate different policies. Since each agent is inherently autonomous and interacts with different agents and the environment according to a set of rules to achieve its goals, these rules lead to the optimization of agent performances.

In this paper, the agent-based RL algorithm is used to simulate the destination choice of shopping and recreation trips of Qazvin citizen activity tours. Firstly, 12 activity patterns were extracted from the survey data of the Qazvin urban transportation master plan (QUTMP). In the second step, the reward which is based on the relative attractiveness of the zones calculated for 12 municipality districts using modes including walking, car, and bus, and the punishment was calculated according to the travel time; with these values simulation of the destination choice of shopping and recreation trips was performed according to the value of Q for each district. The implementation of the destination choice simulation algorithm demonstrates the good performance of this algorithm (the correlation coefficient was above 0.9 for both shopping and recreation purposes); Furthermore, the simulation findings and survey data show a consistent pattern across districts, demonstrating that the simulation result has realistic implications and should be used further in transportation planning.

In this paper, it was assumed that travelers depart from the origin to the destination and the effect of middle districts was ignored due to the data limitations. In future studies, it is recommended to gather data in more detail using questionnaires to achieve the route of trips from origin to final destination. Also, the impacts of attraction degree of districts and travel time may vary from one person to another one. In the future, particular surveys can be conducted to determine the weight of each factor. This would help to enhance the accuracy of shopping and recreation destination choice modeling.

Acknowledgment

The authors are appreciative of Qazvin Municipality, the Deputy of transportation and traffic for providing the data for this study.

References

[1] M. Abbasi, M.H. Hosseinlou, S. JafarzadehFadaki, An investigation of Bus Rapid Transit System (BRT) based on economic and air pollution analysis (Tehran, Iran), Case Studies on Transport Policy, 8(2) (2020) 553-563.

[2] A. Tayarani Yousefabadi, A. Mahpour, I. Farzin, A. Mohammadian Amiri, The Assessment of the Change in the Share of Public Transportation by Applying Demand Management Policies: Evidence from Extending Traffic Restriction to the Air Pollution Control Area in Tehran, AUT Journal of Civil Engineering, (2020).

[3] H. Ding, W. Wang, M. Yang, Application of an agent-based modeling to simulate destination choice for shopping and recreation, Procedia-Social and Behavioral Sciences, 96 (2013) 1198-1207.

[4] J. de Dios Ortúzar, L.G. Willumsen, Modelling transport, John Wiley & sons, 2011.

[5] S. Kikuchi, J. Rhee, D. Teodorović, Applicability of an agent-based modeling concept to modeling of transportation phenomena, Yugoslav Journal of Operations Research, 12(2) (2002) 141-156.

[6] A.N. Koushik, M. Manoj, N. Nezamuddin, Machine learning applications in activity-travel behaviour research: a review, Transport reviews, 40(3) (2020) 288-311.

[7] A.R. Tavares, A.L.C. Bazzan, Reinforcement learning for route choice in an abstract traffic scenario, in: VI Workshop-Escola de Sistemas de Agentes, seus Ambientes e aplicaçoes (WESAAC), 2012, pp. 141-153.

[8] F. Wei, S. Ma, N. Jia, A day-to-day route choice model based on reinforcement learning, Mathematical Problems in Engineering, 2014 (2014).

[9] Z. Zhang, J.-M. Xu, A dynamic route guidance arithmetic based on reinforcement learning, in: 2005 International Conference on Machine Learning and Cybernetics, IEEE, 2005, pp. 3607-3611.

[10] D. Charypar, K. Nagel, Generating complete all-day activity plans with genetic algorithms, Transportation, 32(4) (2005) 369-397.

[11] S.H.R. Hajiagha, S.S. Hashemi, Y. Mohammadi, E.K. Zavadskas, Fuzzy belief structure based VIKOR method: an application for ranking delay causes of Tehran metro system by FMEA criteria, Transport, 31(1) (2016) 108-118.

[12] A. Rasaizadi, I. Farzin, F. Hafizi, Machine learning approach versus probabilistic approach to model the departure time of non-mandatory trips, Physica A: Statistical Mechanics and its Applications, 586 (2022) 126492.

[13] E. Alvarez, J.G. Brida, An agent-based model of tourism destinations choice, International Journal of Tourism Research, 21(2) (2019) 145-155.

[14] B.J. Vitins, A. Erath, Destination choice modeling with spatially distributed constraints, in: 19th Swiss Transport Research Conference (STRC 2019), STRC, 2019.

[15] A.L. Bazzan, R. Grunitzki, A multiagent reinforcement learning approach to en-route trip building, in: 2016 International Joint Conference on Neural Networks (IJCNN), IEEE, 2016, pp. 5288-5295.

[16] M. Yang, Y. Yang, W. Wang, H. Ding, J. Chen, Multiagent-based simulation of temporal-spatial characteristics of activity-travel patterns using interactive reinforcement learning, Mathematical Problems in Engineering, 2014 (2014).

[17] D. Janssens, Y. Lan, G. Wets, G. Chen, Allocating time and location information to activity-travel patterns through reinforcement learning, Knowledge-Based Systems, 20(5) (2007) 466-477.

[18] F. Zuo, K. Ozbay, A. Kurkcu, J. Gao, H. Yang, K. Xie, Microscopic simulation based study of pedestrian safety applications at signalized urban crossings in a connected-automated vehicle environment and reinforcement learning based optimization of vehicle decisions, Advances in Transportation Studies, (2020).

[19] C. Chen, W. Chen, Z. Chen, A Multi-Agent Reinforcement Learning approach for bus holding control strategies, Advances in Transportation Studies, (2015).

[20] R.S. Sutton, A.G. Barto, Reinforcement learning: An introduction, MIT Press, 2018.

[21] M. Botvinick, S. Ritter, J.X. Wang, Z. Kurth-Nelson, C. Blundell, D. Hassabis, Reinforcement learning, fast and slow, Trends in cognitive sciences, 23(5) (2019) 408-422.

[22] U. Wilensky, W. Rand, An introduction to agent-based modeling: modeling natural, social, and engineered complex systems with NetLogo, MIT Press, 2015.

[23] H.M. Schwartz, Multi-agent machine learning: A reinforcement approach, John Wiley & Sons, 2014.

[24] Qazvin urban transportation master plan (QUTMP) Modeling and calibration of travel demand models, 2012.

[25] S. Askari, F. Peiravian, N. Tilahun, M. Yousefi Baseri, Determinants of users' perceived taxi service quality in the context of a developing country, Transportation Letters, 13(2) (2021) 125-137.

HOW TO CITE THIS ARTICLE

I. Farzin, M. Abbasi, A. R. Mamdoohi, An Agent-Based Simulation for Destination Choice of Discretionary Tours: Evidence from Qazvin, Iran, AUT J. Civil Eng., 6(1) (2022) 51-62.

DOI: 10.22060/ajce.2022.20125.5760