Int. J. Nonlinear Anal. Appl. 14 (2023) 11, 333–342
ISSN: 2008-6822 (electronic)
http://dx.doi.org/10.22075/ijnaa.2023.29603.4213

Transport network traffic management and urban travel demand to reduce air pollution (Case study: Shiraz)

Mohammad Bagheri, Hossein Ghafourian, Morteza Kashefioasl, Mohammad Taghi Sadatipour, Mohammad Rabbani

Department of Environmental Engineering, North Tehran Branch, Islamic Azad University, Tehran, Iran

(Communicated by Seyyed Mohammad Reza Hashemi)

Abstract

Today, air pollution and energy consumption are metropolitans' main transportation issues. In these cities, most people consider their mode of transportation based on the appropriate means, including passenger, travel characteristics, population growth, urban space, and transportation. Therefore, the systematic optimization of travel demand in the actual road network in urban areas is necessary. Travel Demand Management (TDM) is one of the well-known methods to solve these problems in congested areas. TDM is a strategy to reduce the efficiency of the urban transportation system by granting special concessions to public transportation methods, implementing the ban on private cars in certain places or times, and increasing the cost of using some facilities such as parking in busy areas pricing network. Transportation demand management is one of the most effective methods to reduce traffic and control air pollution, especially in crowded areas of the city center. A few studies have optimized urban transportation in congested cities by combining Markov decision processes based on decision processes with reward and evolution-based algorithms and simultaneously considering customers and travel characteristics. Therefore, this study provided a new network traffic management for urban cities with multiple objective functions related to the expected reward value of the Markov decision system using a genetic algorithm. Shiraz is considered as a benchmark to evaluate the performance of the proposed approach. Then, the impact of toll levels was evaluated on changes in user and operator cost components.

Keywords: Traffic management, Transportation network, Travel demand, Decrease air pollution
2020 MSC: 49Q22

1 Introduction

The increasing population and urbanization have led to the centralization of government and economic activities in cities, usually in their center. This issue causes problems in transportation, including the traffic of cars in city centers and the lack of parking space for this volume of traffic, increasing the fuel consumption of vehicles, leading to environmental pollution and threats to human physical health.

Therefore, regulating the traffic flow of cars in dense urban areas is one of the critical issues in urban transportation management. Every day, congestion occurs in various places, such as grocery store queues, public telephone queues, and traffic queues created during peak traffic hours. All people have experienced injuries caused by traffic congestion.

Email addresses: mohammadbagheri.ikiu@gmail.com (Mohammad Bagheri), ghaforian25@yahoo.com (Hossein Ghafourian), mortezakashefialasl@gmail.com (Morteza Kashefioasl), m_sadatipour@iau_tnb.ac.ir (Mohammad Taghi Sadatipour), mhd_rabani@yahoo.com (Mohammad Rabbani)

Received: April 2022 *Accepted:* January 2023

There is an essential difference between the grocery store and road traffic congestion. A grocery store can increase capacity during busy hours by hiring more employees. However, the road capacity is fixed, and increasing the road capacity requires significant investments, which are not Cost-effective in most cases. For example, a road with 1500 vehicles per hour will not have a capacity problem crossing 1400 vehicles. Traffic may flow slowly on that road, thus increasing travel time. However, people choose the route that reduces their travel time as much as possible. However, there may be 1,600 vehicles entering this road during peak traffic hours. At this moment, congestion occurs, and the speed of the traffic rate decreases drastically, and as a result, the travel time increases [2].

In recent decades, cities have developed due to people's desire to live in cities and use urban facilities. People have turned to use private vehicles for easier access to city facilities. Since the growth of the urban population has not been consistent with the expansion of transportation facilities and networks, congestion has increased dramatically. Thus, governments have been required to use the opinion of transportation experts to reduce the adverse effects of congestion on society. Congestion appears when the demand to use the route exceeds the capacity of the infrastructure considered in that route. There are two ways to deal with it: increasing capacity and demand management. Since developing intra-city roads and communication lines between them is practically expensive, governments and policymakers should seek to choose less costly methods to improve the current situation [6].

Transportation is one of the most critical issues of the human day, which needs to increase movement speed. The problems caused by this increase in the transportation system, including air pollution, are among the most complex issues of human life, especially in the big cities of the world, where hundreds of thousands of people often live. Further, the increasing growth of these cases is speedy. Thus, a lack of taking control measures leads to complex and unsolvable crises, and their consequences will seriously affect the residents of cities and their living ecosystems.

This study adopted particular policies for this issue, considering the effect of reduction of travel demand on decreasing network traffic, especially in the central business district (CBD), and increasing travel supply. In addition, taxing all users equally is contrary to social justice since it should be based on how much network facilities are used and the amount of pollution caused. Vehicle motorization, insufficient traffic management strategies, and inappropriate land use and transportation planning have caused city traffic congestion. This density has increased the travel time in the town, excess fuel consumption, increased pollution, and deterioration of the urban environment for the lives of its residents, which is contrary to the principles of sustainable development. Human exposure to polluted air for a long time - especially airborne particles - increases chronic respiratory diseases and various cancers, and human health (both mentally and physically) is threatened. Studies have shown such a situation in the urban areas of today's world.

The relationship between urban transportation and urban sustainability is a topic that does not require much argument to prove its existence. All city dwellers, without exception, use the transportation system in the city, and at the same time, they face transportation problems. Urban transportation is an essential element in the quality of life, and it is practically impossible to ignore such an important and influential element in the lives of urban residents in urban planning and management. Therefore, the issue of transportation and urban traffic should be carefully studied, and necessary planning should be done in different dimensions to remove obstacles to urban sustainability, sustainable development, and sustainable city. For example, according to the sample studied in this research, 60% to 80% of air pollution in Tehran is related to 11 million and 500 thousand intra-city trips and the traffic of 3 million and 600 thousand cars in this city. Meanwhile, the streets of this city have a capacity of only 495,000 cars. Therefore, today the roads of Tehran are more than seven times their capacity under the passage of cars 3. Such a situation in Tehran is one of the indicators of its lack of urban sustainability, and suitable solutions should be provided under its geographical and human conditions to remove obstacles to sustainability.

Cao et al shows that Based on the cell phone mobile signaling data, urban air quality observation data, and urban transportation infrastructure environment data of Nanjing, and through the panel regression model and the standard deviation ellipse analysis (SDE), measure the impact of air pollution on residents' daily traffic vitality by constructing a survey panel matrix data system with streets as spatial units. This study shows that under different transportation models and different location conditions, there are obvious differences in traffic vitality. The entire city presents a trend of "northeast-southwest" axial expansion in the spatial pattern of the traffic vitality. Compared with the urban core area, the traffic vitality of residents in the north-south areas of Nanjing's periphery has declined significantly. Also, the inhibitory effect of air pollution on public traffic vitality and self-driving traffic vitality are differences. Approximately one-tenth of traffic activities may be inhibited by air pollution. The weakening of traffic vitality greatly reduces the city's ability to attract and gather people, materials, and resources [1].

Soleimani et al. and coworkers shows that Among the various methods of travel demand management, congestion pricing is a very efficient measure. In this study, it is tried to simultaneously increase the efficiency of the transportation network and reduce the environmental effects by using a bi-level model for the multi-modal network. The genetic and

Frank-Wolfe algorithms have been used to solve the bi-level programming model. The proposed algorithm is also applied for a real network in Isfahan, Iran. The results of the proposed model for different pricing strategies were compared. According to the results, both 28 pricing schemes mitigate traffic congestion and pollution, and the demand was shifted from the private car mode to public transportations. However, link-based pricing provides better performance than cordon-based pricing. According to the results, if there are conditions of link-based pricing, this scheme can reduce pollution and increase tolls revenue [8].

Kai Huang et al paper's reviews the development status of smart transportation system construction and identifies three research directions: smart parking, smart roads and smart transportation management systems, this study aimed to establish a systematic framework for representative transportation scenarios and design practical application schemes. In this study, proposed a smart transportation system based on smart parking, roads and transportation management in urban areas, and by analyzing application scenarios, analyzed and predicted the development directions of smart transportation in the fields of smart parking, roads and transportation management systems occured [5].

2 Research literature

Hekmatnia et al. [3] investigated the environmental management of urban waste transportation in Yazd using WAGS software. Most of the solid waste management budget was spent collecting and transporting such wastes, which caused additional costs and wasted time. Municipal policies were established to optimize the waste management system and improve solid waste collection and disposal. Yazd's budgets for the next 15 years, including the capital needed to supply machines, the capital needed to repair and maintain machines, and the capital required to cover staff costs, were calculated to achieve the defined goal using WAGS software. The results showed that the highest waste collection costs are related to the staff (50.95%), following machinery supply capital (39.62%), repair costs (4.93%), and fuel supply costs (65.2%). The total collection costs during 15 years were equal to 176,700 million rials, which required 151,497 million rials of additional investment by 1200.

The cost of collecting and transporting to the burial site is 260 Rials per kilogram of waste, including all the expenses of employees, collection machines, fuel, and repairs. Finally, the collection cost of each household was equal to 67,570 rials during the year [3].

Hosseini et al. [4] prioritized the effective components of transportation management on city traffic with an economic perspective and the application of the AHP method. The population included experts in various service, economic, social, and military fields (100 people), and 50 were selected for pairwise comparisons using the purposeful quota sampling method. Information was collected through a questionnaire, and the data were analyzed using the AHP technique and Expert Choice software. The results showed that the priority component of access over movement reduces traffic and costs as an essential element in Tehran's transportation and urban traffic management. Therefore, movement at different levels and the spectrum of public transportation should transit main components in policies, prioritizing urban programs to reduce costs.

Yadollahi et al. [9] investigated the role of the emergency transportation management system in Tehran. According to the definition of the needs of the transportation system in crisis conditions, the system was divided into two views of the type of transportation system and classification based on the system components. The incidents affecting the transportation system were classified based on the origin of occurrence and the type of damage on the amount of supply and demand. Understanding the nature of natural disasters, evaluating the impact of these disasters on the transportation network, and providing management methods and effective solutions to prevent the occurrence of crises were among the goals of this research. The concepts of supply, network, and vulnerability were first mentioned, and the definitions of the network were presented based on different parameters to examine the accidents' results on the transportation network's supply. In addition, factors affecting the reduction of the supply of the transportation network, which is divided into three different groups, have been identified. The necessary suggestions were presented to reach the desired situation based on the condition of each component and measuring its efficiency.

Portalebi et al. [7] presented a behavioral model of the choice of business travel style under the influence of management policies. This research aimed to evaluate the simultaneous effects of congestion pricing and public transportation improvement policies on the users' mode of choice. The data, including two categories of revealed and expressed preference information, which was collected from 25 respondents from even or odd districts of Tehran. The revealed preference data included information on the status of the transportation facility, and the expressed preference data were the users' choices in dealing with new policy conditions.

3 Method

This problem was formulated as a Markov decision system and solved for the decision variables. The following sections outline the steps for problem definition and formulation. Suppose, $\{X_n, n \in N\} = Xs$ a Markov chain with state space $E(|E| = m)$. Assume that the transition from state i to j occurs with probability $p(i,j)$ and that this event is accompanied by reward $r(i,j)$ (positive or negative). Therefore, according to the nature of X, the reward R exhibits a random nature.

Assume that $v^n(i)$ is the mathematical expectation of the reward after n transitions of the system; so:

$$v^n(i) = \sum_{j=1}^{m} p(i,j)[r(i,j) + v^{n-1}(j)] \tag{1}$$

Now suppose $q(i) = \sum_{j=1}^{m} p(i,j)$. Using z transformation analysis on Equation (1) for large n:

$$v^n(i) = ng(i) + v(i), i \in E \tag{2}$$

In which, $v(i)$ is the asymptotic value of $v^n(i)$ when n tends to infinity and:

$$g(i) = \sum_{j=1}^{m} s(i,j).q(j), i \in E \tag{3}$$

In which, S is a random matrix with members s(i,j), and the ith row is the probability of the system being limited in state $j \in E$ starting from $i \in E$. Then $g(i)$ can be defined as the mathematical expectation of the system reward when the system starts from state i and returns to state i after several iterations. If the system is completely Goodwick, all the rows of the matrix S will be the same, and all the states will have the same income. In other words, for all i:

$$g = \sum_{j=1}^{m} \prod(j)q(j) \tag{4}$$

In which,$\prod(j)$ is the probability of the system being limited to state j for large n, which can be written as the following expression:

$$v^n(i) = ng + v(i), i \in E \tag{5}$$

Suppose $k = 1, 2, \ldots, k$ candidates are available in each of the i states. The transition matrix Pk and the reward matrix Rk should be known for each k candidate. Further, $(i,j)Pk$ and (i , j) Rk are the probability and reward of moving from state i to state j when decision k is taken. The operator should make the best decision in each step (day) n and state i of the system in such a way as to maximize the total reward during the interval $[0, n]$. The set is called a policy for all i's and n's as $\{d_i^n I \in E \ and \ = 0, 1, 2, \ldots\}$. d_i^n represents the candidate (number) selected at stage n when the system is placed at stage i. Therefore, the problem becomes $\{d_i^n\}$.

$$\begin{aligned} v^{n+1}(i) &= max_k \sum_{j=1}^{m} p^k(i,j)[r^k(i,j) + v^n(j)] \\ &= max_k[q^k(i) + \sum_{j=1}^{m} p^k(i,j) + v^n(j)], i \in E, N = 0, 1, 2, ... \end{aligned} \tag{6}$$

In which, $q^k(i) + \sum_{j=1}^{m} p^k(i,j)r^k(i,j)$ corresponds to R^k and P^k.

Consider a specific policy $\{d_i^n = K\}$ corresponding to the known matrices Rk and Pk for the limiting behavior of the system. Therefore, according to Equations (1) and (5):

$$g = q^k(i) + \sum_{j=1}^{m} p^k(i,j)[v(j) - v(i)], i = 0, 1, 2, ..., m \tag{7}$$

Equation (7) gives a set of $1 + m$ unknowns and m linear equations, which can be solved for g and the relative values of $v(i)$ assuming $v(m) = 0$. It is possible to find the optimal policy using equation (6) and $ng + v(i) = vn(i)$ for large n by maximizing the right side of the following expression for candidate k with the value of g and the relative values of $v(i)$ from state i and time (step) $1+n$:

$$g+v(i)=max_k\{q^k(i)+\sum_{j=1}^{m}p^k(i,j).v(j)\}, i\in E \tag{8}$$

Howard (1) proved that the stopping condition for the calculations could be realized when the obtained policy is the same as the input of Equation (7). Therefore, the optimal policy leads to the limit of the maximum average daily reward. Otherwise, this process is iterated by placing the new policy in Equation (7).

Howard (1) described this iterative method as follows:

3.1 HP method

Step 0. Initialization: R and P matrices are known for different k.

Step 1: value determination: Obtain the policy d corresponding to the matrices P and R, and q(i) is obtained based on the following equation.

$$q(i)=\sum_{j=1}^{m}p(i,j)r(i,j), i\in E \tag{9}$$

Then, the relative values of $v(i)$ and g are determined based $v(m)=0$ and the following equation:

$$g+v(i)=q(i)+\sum_{j=1}^{m}p(i,j)v(j) \tag{10}$$

Step 2. convergence condition: when the policy $d^*=d$, stop the algorithm. In this case, the optimal policy is obtained. Otherwise, set d* = d and return to step 1.

Until the end of this algorithm, the value of g in each iteration becomes larger than the previous iteration, and d* has the highest value of g and the average daily reward. Since the number of all these policies is limited, the algorithm is stopped in a few iterations.

3.2 Reward matrix

Consider a case where O/D demands lead to short-term, fixed results. Further, assume that short-term decisions are just state changes. Then, the reward obtained by air pollution control decision k is the sum of the two performance measures.

1. Air quality change criterion from state i to state $(i,j\in E)$ j. This measure is calculated using the level of carbon dioxide in the environment.
2. Lower transportation cost criterion (less time)

This decision is related to the change in the cost of private cars entering an area, which can influence the decisions of these drivers on the choice of mode. When the cost-to-pollution ratio increases due to stagnant air in the city, the cost increase forces private car drivers to use public transportation in whole or partial ways.

The environment of the problem and its sensitivity to human decisions in terms of price were described extensively. The model presented below is the only model that can be cited in this research, which was developed to perform calculations with the final transportation model. Therefore, some of its components can be changed.

3.2.1 Mode selection models

The mode selection model is a multivariate logit function, which can be expressed as the following equation:

$$Pr_{ks}^{pm}=\frac{e^{U_{ks}^{pm}}}{\sum_{n=m}U_{ks}^{pm}}; \forall m\in M, \forall(k,s)\in P \tag{11}$$

In which, Pr_{ks}^{pm} is the probability of choosing m for one travel with the objective of p from origin k to destination s, representing one unit U_{ks}^{pm}. M indicates the set of available states, and P is the set of origin/destination (o/d) pairs. The utility function U_{ks}^{pm} is a function of the variables/characteristics of states (e.g., travel time), passengers (private car drivers), and the purpose of travel (work).

The costs of private cars at a restricted zone intersection negatively affect these modes' benefits. In this research, only travels starting from an origin outside the prohibited area and destinations inside these areas are automatically priced. Several tests have shown that drivers of private cars with origin and destination outside the prohibited area with the shortest route within the intersection are preferable to using private cars and changing the route without passing through the prohibited areas or using public transportation from the beginning. Therefore, the new shared mode is calculated for these drivers by calculating the travel times corresponding to the new shortest routes outside the pricing zones for private cars and the cost using other modes. Then, the reduced estimation of private car passengers is directed towards public transit mode or car parking mode and using public transport.

Some passengers of private cars from origin k to destination s for destination p.w_{ks}^{p} represents the willingness to pay a specific cost, which is the inverse function of cost–s, as follows:

$$w_{ks}^{p} = exp(-a(\frac{\tau}{D_{ks}})^{b})a, b > 0 \tag{12}$$

In which, τ is is the cost of entering the area, D_{ks} is the distance of the shortest network from the origin k to s, and a and b are the two parameters of this function.

Suppose y_{ks}^{p} chooses a part of the automatic request timing to change the mode and select the public transition or the mode of parking the car and using public transportation and $1 - y_{ks}^{p}$ according to the s-shaped change diagram.

$$y_{ks}^{p} = exp(c - \frac{\tau}{D_{ks}})^{d})\ c, d > 0 \tag{13}$$

In which, c and d are the two parameters of the above function. Increasing τ per distance unit (Dks) decreases w_{ks}^{p}. Therefore, the value of w_{ks}^{p-1} and y_{ks}^{p} increases as a result $w_{ks}^{p-1}\ y_{ks}^{p}$. Most likely, the value $(1 = w_{ks}^{p})(1 - y_{ks}^{p})$ will also increase. The last two mentioned features are, respectively, the share of passing and parking the car and the use of public transport and the share of taxis from automatically directed requests. The fraction of automatically directed requests for a target p that is attracted by public transit or the mode of car parking and use of public transportation and decides to use the transition time mode at least from k to s t_{KS}^{b} or the equivalent time of car parking and using public transportation $\beta_{P/R} = t_{K,P/R}^{a} + t_{P/R,S}^{b} + t_{KS}^{PR}$. Other algorithms are also suitable, but a binary representation is used due to the simplification of the problem in building the model. In the above expression, P/R represents the nearest car parking location on the route from origin k to destination s. $t_{K,P/R}^{a}$ is the shortest automatic travel time from the origin k to the nearest parking lot on the route, $t_{P/R,S}^{b}$ is the shortest transition time from the car parking lot to the destination s. CP/R is the fair cost of transit and parking, converted to an equivalent travel time using a conversion factor, and β is the inverse of the amount of travel time.

3.2.2 Automatic performance fee

Auto operation costs are supplemented by repair, maintenance, performance, investment, and insurance/accident costs. Assume that the $\bar{c}$ represents the average cost of units per distance traveled by private cars. Therefore, the cost of automated operation per hour per decision k (c_{opa}^{k}) can be calculated as the following equation.

$$c_{opa}^{k} = \bar{c}(X^{'1} - X^{'k}) \tag{14}$$

In which, $X^{'k}$ is is the distance traveled by private cars in kilometers per hour for decision k, and we have no choice for k=1.

3.2.3 Monetary cost equivalent to travel time

Assume that C_t is the amount of travel time of a person and C_{ta}^{k} is the monetary cost equivalent to the total travel time of the non-transitory for decision k. Then:

$$C_{ta}^{k} = c_t(y^1 - y^k) \tag{15}$$

In which, Y^k is the travel time of all vehicles except buses (in hours) for decision k, and $k = 1$ has no alternative.

$$Y^k = \sum_{m \in M, m \neq bus} \tag{16}$$

In which, α^m shows the average occupancy rate (passenger per vehicle) in mode m and Y^{mk} is the travel time of mode m per decision k.

It is assumed that $\bar{Y}^k$ is defined as the total travel time of a public passenger (bus) (in terms of passengers per hour) under decision k. Therefore, the monetary cost equivalent to the total travel time of the public traveler in the network can be expressed as follows:

$$C_{ta}^k = c_t(\bar{Y}^1 - \bar{Y}^k) \tag{17}$$

$\bar{Y}^1 > \bar{Y}^k$ and $\bar{Y}^1 < \bar{Y}^k$ are expected totally.

3.2.4 Reducing cost in car passenger units

Assume Q as the maximum number of private cars for the O/D pair, which is the demand function in Figure (2). Then, an estimate of the costs of car passengers to change the car to a lower mode is made. When (p,q) shifts to a new equilibrium point $(p*, q*)$, the reduction in the surplus received is as follows.

$$\Delta C_{cs} = \int_0^{p*} q.dp = \int_0^{p*} d(p).dp \tag{18}$$

At the price p, q, passengers tend to drive their cars. When the price increases to $p + dp$, the demand for cars decreases to $q - dq$, and dp passengers who are willing to pay price p to use their private cars, their price increases from p to$p + dp$. An approximate measure of ΔC_{cs} can be obtained experimentally according to the following relationship by the transport model presented in this research.

$$\Delta C_{cs} = \sum_{k=1}^{k^0} \frac{(q^k + q^{k+1})(p^k - p^{k-1})}{2}.p = \tag{19}$$

In which, q^k is the demand for a private car when the price of entry into the restricted area is p^k under decision k.

4 Results

The use of network pricing is one of the most effective methods of reducing traffic and air pollution, especially in crowded areas of the city center. The proposed method is to select the optimal strategy by genetic algorithm for intra-city trips in high-traffic areas according to the state of air pollution in spring, autumn, and winter. According to the air pollution situation, the amount paid by private car drivers who enter the traffic plan area increases or decreases. The Multi-User Equilibrium (UE) model was used to find the optimal cost for P/R units of private cars and high-traffic areas and traffic allocation.

Private cars and high-traffic areas were used to find the optimal cost for P/R units. In addition, network pricing is one of the most effective ways to manage transportation demands to reduce traffic and control air pollution, especially in crowded areas of the city center.

Parameters such as distance traveled by bus and private cars, the fuel cost of private cars and buses, total travel time by bus and car, and environmental pollution costs were considered to find the optimal Markov decision matrices.

4.1 Simulation results

The case study was related to Shiraz, Iran, with a 1.3 million population in 2004. The studied area had 189 regions, 156 of which were located inside the city. First, this area (internal and external) was divided into 14 internal areas and 1 external area. Figure 1 shows 156 areas inside the city and its 15 districts. In this figure, the bold area represents the high-traffic area of the city.

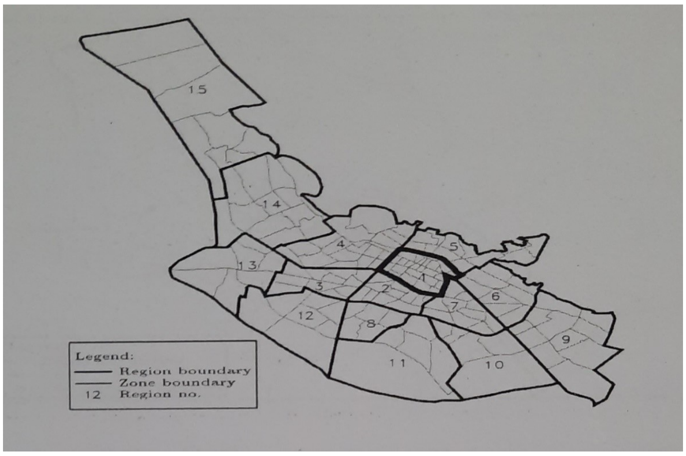

Figure 1: The studied areas in Shiraz and its corresponding areas.

Travel demand was investigated in the early morning hours of a weekday in 2006. The transportation system consisted of a network of roads and roads, designed for two types of transportation, including buses and private cars, with 1078 nodes, 1611 two-way roads, and 200 one-way roads. Figure (2) presents the studied road network in which the hachured area is considered the forbidden area and the city's economic center. The public transportation network consists of 73 special bus lines and 382 regular buses. The road network of this transportation network is of FHWA type, the amount of traffic x and the time required to reach from the beginning of the link to its end t follow the equation (21).

$$t = a + bx^4 \tag{20}$$

The traffic allocation to these links is implemented in MATLAB software.

Figure 2: The studied areas, along with the prohibited area and location of private car parking spaces.

This research assumes that the cost of using the CBD area for private cars is known. A total of 10 private parking spaces are provided for private car passengers who prefer to park their cars at these terminals and use the bus system to reach the city center.

4.2 Pricing strategy using Markov decision

A dynamic pricing model is proposed using a hidden Markov decision-making model to find the optimal strategy for air pollution and traffic control in Shiraz. The reward matrix for the Markov model is determined by weighting each of the mentioned factors in different weather conditions. The optimal price for the Shiraz CBD area changes based on these weights. The state of air pollution of the city varies from state i to state j every day and for every level k related to the cost of entering the CBD restricted area, considering the weather conditions from the reward matrix $R^k(i,j)$. The way of weighting different factors to calculate the $R^k(i,j)$ matrix is as follows:

1. Profit related to the operator

This benefit is related to the amount of consumption of limited gasoline and diesel fuel resources, which are represented by D^k and R_k values, respectively, and is considered with the weight ω_{re} in the reward matrix. This factor depends only on the decision k and changes based on the simulation results, as shown in Figure (4).

The next factor is the total benefit with the impact factor ω_p with two sub-criteria related to the benefit of air health and the benefit of the passengers of this transportation network. The total benefit is represented by H_j, considering the criterion of healthy air in state j, and is calculated from the following equation:

$$H_i = \left\{ \begin{array}{c} 1; ifj = 1 \\ 0.5; ifj = 2 \\ 0; ijj = 3 \end{array} \right\}. \tag{21}$$

The benefit of passengers is also categorized into two sub-criteria of annual performance benefit and reduced comfort of private car drivers. The resulting profit is the annual performance profit of the distance traveled by private cars in the network VK^k the travel time by bus Tp^k and the travel time by private cars Tnp^k which is considered with the impact factor ω_{uc}. The decrease in the comfort of private car drivers can be considered as the cost of passengers with the weight ω_{uc} in the calculations related to the determination of the reward matrix using the following equation:

$$R^k(i,j) = \omega_{re}(D^k + G^k) + \omega_{ph}(H_j) + \omega_{uo}(VK^k + Tp^k + Tnp^k) + \omega_{uc}(CK^k) \tag{22}$$

Howard's method was implemented for different values of ω_{re}. In this method, the value of ω_{ph} changes from 0 to 1. The obtained results are summarized in Table (1), in which the values of ω_{re}, ω_{uo}, and ω_{cs} are also displayed.

Table 1: The optimal decision using Howard's method for different air quality conditions and the effect of profit function parts in different seasons.

Season									Weight			
Spring			Autumn			Winter						
3=i	2=i	1=i	3=i	2=i	1=i	3=i	2=i	1=i	ω_{cs}	ω_{uo}	ω_{ph}	ω_{re}
2	2	2	2	2	2	2	2	2	0:38	0.13	0.00	0.5
2	7	2	2	2	2	2	7	2	0.31	0.10	0.18	0.41
2	7	2	2	7	2	2	7	2	0.30	0.10	0.19	0.41
2	7	2	2	7	2	2	9	2	0.29	0.14	0.22	0.39
2	9	2	2	7	2	2	9	2	0.29	0.14	0.23	0.39
2	9	2	7	7	2	2	9	2	0.29	0.10	0.24	0.38
7	9	2	7	9	2	7	9	7	0.28	0.09	0.25	0.38
7	9	7	7	9	2	7	9	7	0.27	0.09	0.27	0.37
7	9	7	7	9	7	7	9	7	0.26	0.09	0.32	0.34
7	9	7	7	9	7	7	9	9	0.23	0.08	0.40	0.30
7	9	7	7	9	7	7	10	9	0.21	0.07	0.43	0.29
7	9	9	7	9	7	7	10	9	0.21	0.07	0.44	0.28
7	10	9	7	9	7	10	10	9	0.20	0.07	0.47	0.27
10	10	9	7	9	7	10	10	9	0.19	0.06	0.50	0.25
10	10	9	7	9	9	10	10	9	0.18	0.06	0.15	0.25
10	10	9	10	9	9	10	10	9	0.18	0.06	0.52	0.24
10	10	9	10	10	9	10	10	9	0.17	0.06	0.55	0.23
10	10	9	10	10	9	10	10	10	0.12	0.04	0.68	0.16
10	10	10	10	10	9	10	10	10	0.11	0.04	0.72	0.14
10	10	10	10	10	10	10	10	10	0.28	0.4	0.79	0.11

According to Table (1), the following results can be deduced:

1. The optimal value of a higher price level is obtained by increasing the impact factor ω_{ph}, which increases the number of bus passengers.

2. The decision variable of the price level of the CBD prohibited area is equal to lower values to minimize the cost of transporting passengers when the air quality of the city is high ($i = 1$) using the Markov decision method.
3. The value of the decision variable provides a higher price level of the CBD restricted area to prevent further deterioration of the city's air quality for the optimal policy for very small values of ω_{ph} when the city's air quality is in an average state ($i = 2$).
4. Lower CBD restricted zone price level values are more optimal due to the increased environmental costs and comfort of private car drivers for unfavorable air quality ($i = 3$). If ω_{ph} has a more significant value, the value of the decision variable will also be significant.
5. Table (4) shows that these policies vary by season because of varying weather conditions. For example, in the winter season and the effect of more air inversion, the value of the decision variable is also significant for lower ω_{ph}. However, in the spring, when the probability of rain and wind increases, the value of the decision variable is small for lower ω_{ph}.

5 Conclusion

In this study, the Markov decision-making process and genetic algorithm were used to increase the profit and choose the optimal price level decision of the CBD prohibited area. The results showed that the proposed presented significantly increased profits in the spring, autumn, and winter. The advantages of the proposed method are:

- The proposed method can provide a more optimal estimate than the previous methods due to the lack of guarantee of past research in obtaining the optimal profit function.
- All passengers use public transportation in optimal conditions based on optimizing the profit function in the genetic algorithm and using Markov decision-making.

References

[1] Y. Cao, H. Wu, H. Wang, D. Liu and S. Yan, *Potential effect of air pollution on the urban traffic, vitality: A case study of Nanjing, China*, Atmosphere **13** (2022).

[2] Y. Ghane, *Providing a suitable analytical method to optimize the combination of density pricing and toll range in cities*, Yazd University of Technical and Engineering Campus: Civil Engineering - Road and Transportation Master's Thesis, 2016.

[3] A. Hekmatnia, A. Karbasi, S.E. Hatef and S.I. Hatef, *Investigating environmental management of urban waste transportation in Yazd using WAGS software*, Envir. Sci. Technol. Quart. (2015) 251–266.

[4] T. Hosseini, Ch. Makani, M. Ariana and S. Mojtabi Abrodi, *Management of transport and urban traffic in Tehran from an economic perspective*, J. Econ. Urban Manag. **15** (2015).

[5] K. Huang, Ch. Jiang, P. Li, A. Shan and J. Wanand Wenhu Qin, *A systematic framework for urban smart transportation towards traffic management and parking*, Electronic Res. Arch. **30** (2022), no. 11, 4191–4208.

[6] H. Mirza Hossein, *Choosing the optimal strategy for intra-city network pricing*, Faculty of Civil Engineering and Technology, Tehran, 2011.

[7] S.E. Seyed Abrishmi, A. Mamdohi and V. Portalebi, *Presenting the behavioral model of choosing the way of business trips under the influence of management policies, a case study; Even or odd area of Tehran city*, Tarbiat Modares University, Tehran, 2014.

[8] M. Soleimani, N. Akbari, B. Saffari and H. Haghshenas, *University of Isfahan Determining urban tolls based on two pricing schemes by considering emission of pollution (Case study: Isfahan, Iran)*, DOI: https://doi.org/10.21203/rs.3.rs-1771235/v1.

[9] M. Yadollahi, M. Puriari and M. Pourreza, *Investigating the role and function of the emergency transportation management system in Tehran*, Transport. Res. Inst., 3rd Int. Conf. Compreh. Crisis Manag. Unforeseen Natural Events, 2016.