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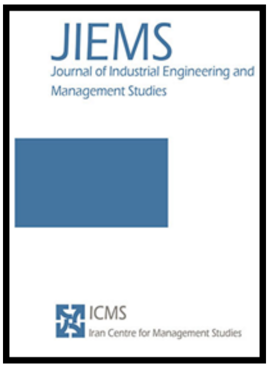

Developing an urban congestion pricing model by considering sustainability improvement and using a multi-objective optimization approach

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Abstract

This paper introduces a Travel Demand Management (TDM) model in order to decrease the transportation externalities by affecting on passengers ‘travel choices. Thus, a bi-objective bi-modal optimization model for road pricing is developed aiming to enhance environmental and social sustainability by considering to minimize the air pollution and maximize the social welfare as its objectives. This model determines optimal prices (bus fare and car toll) and optimal bus frequency simultaneously in an integrated model. The model is based on discrete choice theory and considers the modes’ utility functions in its formulation. The proposed model is solved by two meta-heuristic methods (Non-dominated Sorting Genetic Algorithm-II (NSGA-II), Multi-Objectives Harmony Search (MOHS)) and the numerical results of a case study in Tehran are presented. The main managerial insights resulted from this case study is that its results support the idea of “free public transportation” or subsidizing the public transport as an effective way to decrease the transport related air pollution.

Keywords: Bi-objective optimization; Public transportation pricing; Air pollution; NSGA-II; MOHS.

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1. Introduction

Transportation is a service not a product, so it is impossible to store it for a high demand period (Ortuzar and Willumsen, 2011). Transportation consumption occurs at the same time as its production, therefore, other methods should be considered to manage transportation demand during peak periods.

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Passengers are consumer of transportation and their decisions are affected by price incentives (Karlström and Franklin 2009). Sensitivity of passengers to the price, makes pricing as an effective measure for improving transportation system (Smits 2017).

The first well-known side effect of the urban transportation is traffic congestion, therefore the primary goal of the pricing was to decrease the congestion. Nowadays other transportation externalities are as significant as transportation congestion. For example, road transportation vehicles are the main source of urban air pollution (Bigazzi and Mathieu Rouleau, 2017). Thus, due to the increased transportation externalities, mitigating them has become one of the main goals in pricing implementation (Wu et al. 2017).

Pricing is used for the urban transportation planning (Börjesson, Fung and Stef Proost, 2017). It aims to shift transportation demand from private car (non-sustainable mode) toward public transportation (sustainable) modes (Cats, Susilo and Reimal, 2017). Suitable pricing schemes can make improvement in social welfare (Burguillo, Romero-Jordan and Sanz-Sanz, 2017). It can attract more passengers which makes the service provider to increase public transportation frequency. High frequency decreases waiting time and consequently trip time so it can lead to more passengers using public transportation. It can be said that suitable pricing can result in economies of scale (Mohring, 1972). However, if the service providers fail to increase frequency after a growth in demand, then overcrowding inside the vehicle leads to dissatisfaction of the passengers and as a result transportation demand decreases (De Palma, Kilani and Proost, 2015).

Increasing number of papers in transportation pricing literature shows that authors believe the current transportation prices are not optimal. These prices do not reflect the transportation social cost precisely and there is a room for improvement in pricing scheme especially regarding transportation marginal social and environmental cost related to its externalities such as congestion, air pollution, etc. (Barth and Boriboonsomsin 2008, Johansson-Stenman 2006, Percoco 2013, Zhang, Batterman and Dion, 2011). Thus, it can be said that it is possible to reform current pricing policy by the aim of welfare improvement (Proost and Dender, 2008). However, to the best of our knowledge, there is little research focusing on the optimization models for determining the best prices for road pricing strategies by considering the goal of decreasing the transportation air pollution. The aim of this paper is to include environmental cost of urban transportation in the decision making process, therefore, the air pollution function is included as an objective function in a bi-objective model, with the other considered function being social welfare. Bus fare, bus frequency and car toll are decision variables of the proposed optimization model.

The rest of the paper is organized as follows: section two describes the proposed model by introducing all constraints and both objective functions. Section three explains a case study thoroughly. Section four presents two meta-heuristic algorithms for solving the numerical example related to the case study and their comparisons in details. Section five analyzes the obtained solutions from the managerial point of view, and finally in section six the conclusion is presented.

2. Literature review

Due to the spatial limitations in cities, the supply-oriented development of urban transportation does not consider a sustainable way to improve urban transportation (Liu et al. 2014 (a), Liu, Wang and Meng 2014 (b)). Therefore, the policy makers follow the demand-based developments strategies.

Road pricing was introduced after basic studies of Pigou (1920) and Knight (1924) and is widely supported by both economist and transport planners due to its advantages (Pigou, 1920; Knight, 1924).

Those policies which impose direct cost to road usage are called road pricing. Road pricing is divided into different subsections due to the pricing goals. Those schemes aim to alleviate traffic congestion are called congestion pricing. Congestion pricing is an effective traffic demand management policy (Wei and Sun 2018) which itself is divided into four different types: facility-based scheme, zonal scheme, cordon-based scheme and distance-based scheme (De Palma and Lindsey, 2011).

It is worth noting that although there are lots of theoretical studies in congestion pricing but the number of implementations of congestion pricing are limited mainly due to some public acceptability issues and difficulties in their implementation. For practical purposes often simpler pricing schemes due to less implementation cost and easiness of perception by drivers are preferred (May, 1992). Although there is a considerable literature in congestion pricing regarding its economic aspects, yet it is required to have more studies about empirical assessments of implemented pricing scheme (Parry, 2008).

Additionally, sustainability concept means "to meet current needs in such a way that do not endanger future generation benefits. Sustainable transportation is a transportation system in which the three aspects of sustainability (economic, social and environmental) are considered. The goal of the road pricing is to internalize the external cost of the transportation. That means to force those users who make the externalities to pay for the relative costs. One of the main externalities of congestion is related to its significant contribution to local air pollution levels and consequently to the residents health (Simeonova et al., 2018). The congestion pricing models basically aimed to utilize economic measures to decrease the congestion. But still two other sustainability aspects (environmental and social) are left which shall be considered, Li et al. (2019) proposed two pricing models (cordon pricing and link pricing) by considering the emissions treatment cost. However, their models did not consider the social aspect of sustainable transport.

Therefore, it is necessary to perform studies based on empirical cases of pricing in which optimal pricing is found while simultaneously considering all aspects of sustainability.

2.1. Research gaps and contributions

The main contribution of this paper is in modeling section and its characteristics are as following:

- It is an integrated bi-objective bi-modal optimization with decision variables of price and public transportation design factor aiming to improve transport sustainability.
- It tries to enhance sustainability of a pre-implemented congestion pricing (here cordon pricing) by re-determining car toll, bus fare and bus frequency in a way to improve sustainability.
- It has two objective functions: One aims to minimize air pollution via decreasing total fuel consumptions which increase the environmental sustainability. The other aims to maximize social welfare which includes users (consumers) surplus and service provider surplus simultaneously and improves social sustainability.

- It is not only a toll optimization model but also it determines optimal prices (bus fare and car toll) and optimal designing factor (bus frequency) simultaneously in an integrated model.
- It considers discrete choice theory by using passengers' utility functions for both modes (private car and bus as public transportation).
- It formulates a pricing problem mathematically and uses the data from a case study for solving the model numerically.

3. Problem description

In this paper, a bi-objective bi-modal optimization model is developed to increase sustainability of a per-implemented congestion pricing in a corridor. Therefore, the problem is about re-determining the amount of car toll, bus fare and frequency (of that pricing scheme) in a way to increase environmental and social sustainability of the transportation system.

The model maximizes the social welfare resulting from the transport system with the pricing scheme while minimizing the relative air pollution.

For modeling the demand, a multinomial logit model is used based on passengers' utility functions of bus and private car. The equilibrium constraints are considered such that to show the mutual relationship between travel mode choice and travel time.

3.1. Proposed model

Before presenting the model, the notations (including indices, decision variables and parameters) are defined and then the mathematical formulation of the demand modeling (3.1.2), travel time (3.1.3), Transportation service provider's cost (3.1.4), constraints (3.1.5) and eventually the final model (3.1.6) are presented.

3.1.1. Notations

Indices are:

- i, j : Indices of sections set $\{1,\dots,P\}$
- m,n : Indices of mode set $\{b,c\}$
- b : Indic indicating bus
- c : Indic indicating car

Decision variables are:

- f_b bus frequency in each operation period
- τ_c : car toll (Rial)
- τ_b : bus fare (Rial)

Model inputs and parameters are:

- P : Number of sections in the assumed corridor
- D^{ij} : Total demand from origin i to destination j
- D_m^{ij} : Travel demand from i to j by mode m

- U_m^{ij}: Utility function related to mode m from i to j
- t_{ab}^{i}: Bus access time in section i (hour)
- h_b: Bus headway time (hour)
- t_{vm}^{ij}: In-vehicle time from i to j for mode m (hour)
- α, β : Model coefficients
- C_r^{ij} : Operational cost for travel from i to j by private car (Rials/km)
- O_r : Private car occupation rate
- L_i: Distance between section i and $i+1$ (km)
- t_{m0}^{i}: Travel time from i to $i+1$ in free flow by mode m (hour)
- K_m: Road capacity for mode m
- t_{sb} : Average stop time in bus station (hour)
- C_b: Bus cost function (Rial/bus)
- $W_{driver/h}$: Driver wage(Rial/hour)
- $bFuC_{km}$: Bus fuel consumption (litter/km)
- τ_{bFu}: Gasoline price (Rial/litter)
- Ca_b: Bus capacity
- k : Designing factor
- $f^{\min}, f^{\max}$: Minimum and maximum possible frequency

3.1.2. Model assumptions

In designing the proposed model, the following assumptions are considered:

- A two way corridor with the total length of L which is divided into P sections as shown in Figure 1 is considered.

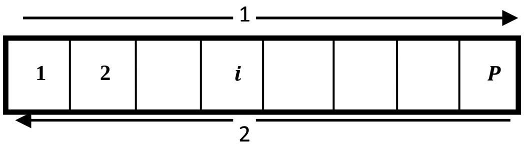

Figure 1. Assumed corridor

- Distance between sections i and $i+1$ is shown as L_i and:

$$L = \sum_{i=1}^{P-1} L_i$$

- Passengers can choose one of the two transportation modes (bus or private car).
- Intermodal shift in one trip is not allowed (trips are done by using only one mode).
- No intersection exists.
- Only one bus station exists in each section.
- Distance between two consecutive sections is the same for both modes.
- Due to existence of specific lane for Bus Rapid Transit (BRT), bus and car traffics are separated.
- Total demand from origin i to destination j shown by D^{ij} ,is constant:

$$D^{ij} = \sum_m D_m^{ij} = D_c^{ij} + D_b^{ij} = constant \qquad (1)$$

- Bus frequency is continuous.
- Bus fare and car toll are constant regardless of Origin-Destination (OD) pair.
- Bus Frequency in both directives is the same. But car demand is different in direction 1 or 2 and it is shown by f_{c1}^{i}.

3.1.3. Demand modeling

There are different types of mode choice models which are related to especial circumstance of each problem. In this model we use passenger utility functions for modes in which the main effective factors are cost and travel time. Theoretically, we assume that U_m^{ij} represents relative utility function of mode m for travelling from origin i to destination j . For bus utility function, following factors are considered: access time, waiting time, in-vehicle time and bus fare. For car utility function in-vehicle time and travel cost (including both operational cost and car toll) are considered. By dividing travel cost to occupation rate, individual utility function is acquired. This can be extended for distance-based toll and fare which are not considered in this paper.

$$U_b^{ij} = \alpha_b + \beta_{ab} t_{ab}^{i} + \beta_{h_b} h_b + \beta_{vb} t_{vb}^{ij} + \beta_{\tau_b} \tau_b \qquad (2)$$

$$U_c^{ij} = \beta_{vc} t_{vc}^{ij} + \beta_c \left(C_r^{ij} + \tau_c\right)/O_r \qquad (3)$$

For utilizing the results of Tehran municipality studies, Multinomial Logit model was used for estimating the demand. So trip number of mode m for OD (i, j) is calculated by the following formula:

$$D_m^{ij} = D^{ij} \frac{e^{U_m^{ij}}}{\sum_n e^{U_n^{ij}}} \forall i,j \qquad (4)$$

According to the welfare literature (Tirachini, Hensher and Rose 2014), the value of the consumer surplus which will be used in social welfare function could be found using the following LOGSUM equation:

$$CS = \sum_{i=1}^{P} \sum_{j=1}^{P} \frac{D^{ij}}{-\beta_c} ln\left(e^{U_c^{ij}} + e^{U_b^{ij}}\right) \qquad (5)$$

In which β_c is the parameter used in car utility function.

3.1.4. Travel time

Since there is a designated route for the buses in this corridor (BRT), the bus and car traffics do not affect each other. Each bus should stop at each station for boarding the passenger and this effects the bus traveling times. Travel times from section i to $i+1$ for bus and car are represented by $t_{vb}^{i}(f_b)$ and $t_{vc}^{i}(f_{c1}^{i})$ are functions of bus frequency and number of cars respectively. For calculating these travel times the following equations, in which $f_{c1}^{i} = \frac{\sum_{l=1}^{i} \sum_{j=i+1}^{P} D_c^{ij}}{O_r}$ equals to number of cars in the lane one of the assumed corridor, are used.

$$t_{vc}^{i}(f_{c1}^{i}) = t_{c0}^{i}(1 + \alpha_0 \left(\frac{f_{c1}^{i}}{K_c})^{\alpha_1}\right) \tag{6}$$

$$t_{vb}^{i}(\mathrm{f}_b) = t_{b0}^{i}(1 + 0.15(\frac{\mathrm{f}_b}{K_b})^4) + t_{sb} \tag{7}$$

3.1.5. Transportation service provider's cost

Some of the transportation service provider's cost are: infrastructure (station, vehicle) cost, human resources cost and operational cost (such as fuel consumption). In this model only variable costs (driver, fuel) are considered. It is assumed that the number of station is constant and the service provider has unlimited access to the bus, therefore, the bus cost is based on bus frequency and gasoline cost according to the following equation:

$$C_b\left(f_b, \tau_{Fu_b}\right) = 2L \times f_b \times bFuC_{km} \times \tau_{Fu_b} + 2f_b \times W_{\frac{driver}{h}} \tag{8}$$

3.1.6. Constraints

This problem has two kinds of demand and frequency related constraints. Constraints 11 to 13 ensures that f_b will be equal or greater than the maximum of total bus demand of all sections in both directions of the assumed corridor. Among these constraints, Ca_b is the bus capacity and k is a design factor which is considered to ensure existence of free capacity for attracting potential demand changes. The bus capacity is determined by the service provider and is an input to the model.

Constraint 14 ensures feasibility of the model due to corridor physical capacity; it means that car demand cannot be greater than road physical capacity.

The bus frequency, which is one of the problem decision variables lies in a boundary. The lower bound value ($f_b^{\min}$) is related to the lowest service level and is defined by the service provider policy. The upper bound value ($f_b^{\max}$) is the maximum frequency which is feasible by the current condition. It is important to note that both of these values are inputs of the model.

Equilibrium constraints 16 and 17 are representing the multinomial LOGIT model used for demand estimation and show the mutual relationship between the travel mode choice and travel time. The travel mode choice is depended on travel time of each mode. This time consequently depends on the demand of each mode which is related to the travel mode choice. These constraints show a fixed-point problem which is solved by iterating between mode choice and travel time until its convergence.

3.1.7. Objective functions and final model

The proposed model is a bi-objective model. It aims to minimize urban road transportation air pollution and at the same time maximizes relative social welfare.

For minimizing air pollution (AP) related to urban transportation, we consider the fuel consumption of the urban transportation system. Since we have two modes (bus and car) in this model, we will consider fuel consumption of both modes. In air pollution function, first term is related to car fuel consumption and second term is for bus fuel consumption. Fuel consumption for each mode is calculated by multiplying number of vehicles in that mode by the distance traveled by these vehicles, and by the average fuel consumption in that mode per kilometer. According to the literature, social welfare function is considered as summation of consumer surplus and producer surplus. Since multinomial LOGIT was used for demand estimation, consumer surplus is obtained by using LOGSUM formula (5), and the producer surplus is equal to the provider revenue minus provider operational cost. The provider revenue is due tothe bus fare and the car toll. Provider cost is the bus operational cost and car operational cost is included in consumer surplus, therefore, the model is as follow:

$$minAP \approx FC_c + FC_b = \left(\sum_{i=1}^{P}\sum_{j=i}^{P}\left[\frac{D_c^{ij}}{O_r}X_c^{ij}\right] + \sum_{i=1}^{P}\sum_{j=1}^{i}\left[\frac{D_c^{ij}}{O_r}X_c^{ij}\right]\right) \times Fu_c + f_b \times X_b \times Fu_b \tag{9}$$

$$maxSW = CS - PS = \sum_{ij}\frac{D^{ij}}{-\beta_c} ln\left(e^{U_c^{ij}} + e^{U_b^{ij}}\right) + \sum_{ij}\frac{D_c^{ij}}{O_r}\tau_c + \sum_{ij} D_b^{ij}\,\tau_b - C_b \tag{10}$$

$$D_{b1}^{i} = \sum_{j=i+1}^{P} D_b^{ij}\ \forall i = 1 to P \tag{11}$$

$$D_{b2}^{i} = \sum_{j=1}^{i-1} D_b^{ij}\ \forall i = 1 to P \tag{12}$$

$$\max_i\{D_{b1}^{i}, D_{b2}^{i}\} \le k f_b Ca_b \forall i = 1 to P \tag{13}$$

$$max\{\sum_{i=1}^{n}\sum_{j=i+1}^{n}\frac{D_c^{ij}}{o_r}, \sum_{i=1}^{n}\sum_{j=1}^{i-1}\frac{D_c^{ij}}{o_r}\} \le K_c \tag{14}$$

$$f_b^{min} \le f_b \le f_b^{max} \tag{15}$$

$$D_c^{ij} = D^{ij}\frac{e^{U_c^{ij}}}{e^{U_c^{ij}} + e^{U_b^{ij}}} \tag{16}$$

$$D_b^{ij} = D^{ij}\frac{e^{U_b^{ij}}}{e^{U_c^{ij}} + e^{U_b^{ij}}} \tag{17}$$

At least two major differences exist between the model presented in this paper and the model proposed in Tirachini, Hensher and Rose (2014). At first, they considered crowding inside bus, but it is ignored in our model. The second one is that our model is a bi-objective model in which the air pollution is considered as an objective function beside social welfare, while they have introduced a single objective model. Thus, contrary to their model, this model cannot be solved analytically due to its complexity. Since, finding the precise solution of bi-objective constrained optimization is not possible, a numerical approach will be considered for solving the proposed model.

4. Case study

The proposed bi-objective model is solved by utilizing the data obtained from transportation of a corridor between Imam Hossein square and Azadi square in Tehran (Figure 2). This corridor is about 9.8 km (6.1 mile) long and is divided into 12 traffic sections (distance of two consecutive sections is approximately 817m). Along this corridor, there is a special lane for BRT. This corridor is part of Tehran bus lane 1, in which each bus completes the cycle (travels from the lane one and returns from the lane two or vice versa) in a two hours period. Regarding the physical limitations of the corridor and the average length of the vehicle (cars and buses), the total capacity of the corridor is assumed to be about 6000 buses and 450 cars.

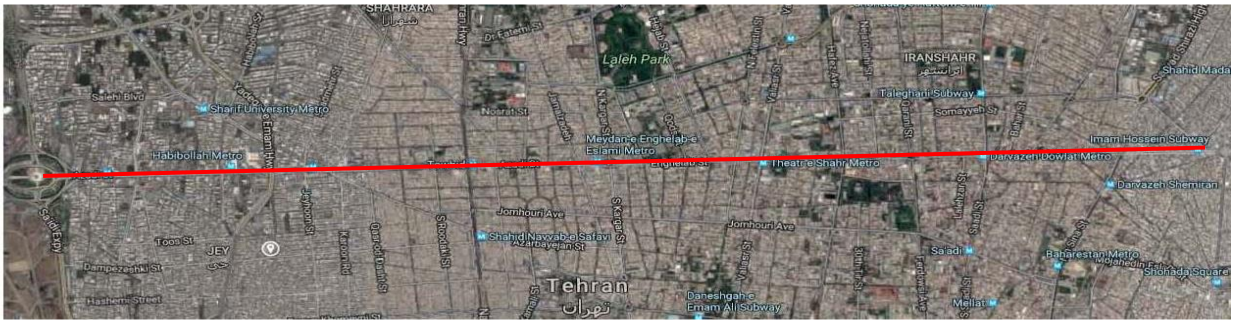

Figure 2. Case study Corridor (From Imam Hossein square to Azadi)

The Origin-Destination (OD) matrix (Table 1) of this corridor was obtained from the studies conducted by Tehran Urban Research and Planning center.

According to the survey conducted by Tehran Municipality in 2012, estimated utility functions for private car and bus are given by the following equations respectively:

$$U_{car}=1.52\times10^{-5}CTT-0.00411CC+1.44COS \quad (18)$$

$$U_{bus}=1.83-0.00655BTTT-0.0342BFC \quad (19)$$

where CTT is the total time of travel by car, CC is the total cost of travel by car, COS is a binary (0 or 1) variable for the rate of car ownership, BTTT is the total time of travel by bus, BFC is the total cost of travel by bus and U_m is the utility function of mode m. The car utility function derived from Tehran Municipality research, includes the same variables as car utility function of this model, except the car ownership variable. Car ownership rate in Tehran is one for each two persons (0.5). Using this rate in the expression (18) will result in a constant value equal to 0.72. The function used in the proposed model does not have constant value, so for similarity and without loss of generality (as utility functions are compared together) this amount will be subtracted from bus utility function. Average bus accessibility time is about 15 minutes (0.25 hour). Bus headway in peak hour is 1 minutes (0.016 hour) and for average (peak and off-peak) is 2 minutes (0.033 hour). Therefore:

$$U_c^{ij} = 1.52 \times 10^{-5} t_{vc}^{ij} - 0.00306(C_r^{ij} + \tau_c) \quad (20)$$

$$U_b^{ij} = 1.108 - 0.00655 \times t_{vb}^{ij} - 0.0342 \times \tau_b \quad (21)$$

In calculating the operational cost of car, only its fuel cost is considered. Therefore, the amount of car operational cost is the multiple of consumed fuel by fuel unit price (now about 10000 Rial/liter):

$$
\begin{aligned}
C_r^{ij} &= X^{ij} \times Fu_{ckm} \times \tau_{Fu_c} \\
&= 0.817|j-i| \times 0.135 \times \tau_{Fu_c} \\
&= 110 \times |j-i|
\end{aligned} \tag{22}
$$

Table 1. OD Matrix for the case study corridor

O/D	1	2	3	4	5	6	7	8	9	10	11	12
1	0	1119	437	254	574	353	619	693	415	681	750	141
2	2009	0	1161	332	1544	1367	2181	485	736	416	167	15
3	456	421	0	798	1015	588	690	195	187	0	50	42
4	356	636	544	0	306	33	387	419	0	54	116	90
5	426	727	110	773	0	736	930	1343	652	527	865	493
6	292	511	13	319	851	0	452	949	719	173	178	29
7	675	156	1255	0	324	455	0	754	728	317	610	284
8	429	961	0	0	264	1216	736	0	279	321	2347	60
9	118	0	0	0	0	258	612	478	0	404	588	279
10	0	0	524	0	24	75	213	1092	350	0	591	352
11	0	201	0	49	327	137	847	726	687	803	0	239
12	30	137	72	0	154	356	149	167	917	450	336	0

Regarding the expression (8), the labor (driver) cost and the bus fuel price (gasoline costs about 3000 Rial/liter), the transportation provider cost will be given by the following equation:

$$
\begin{aligned}
C_b(f_b) &= 2L \times f_b \times bFuC_{km} \times \tau_{bFu} + 2f_b \times P_{driver/h} \\
&= 19.6 f_b 0.598 \times 300 + 2 f_b 6600 \\
&= 13211.7208 \times f_b
\end{aligned} \tag{23}
$$

For in-vehicle time calculation, first, free-flow travel time must be calculated. Regarding maximum allowable speed limit based on Iran national transportation law and assumptions of the model, maximum possible speed of cars and buses are considered as 45 km/hour and 16 km/hour respectively. Thus, in a free flow condition and with maximum allowable speed, private car travels the distance between two sections in 0.0181 hour (about 65 seconds). This time for buses is 0.0510 hour (3.06 minutes).

Average stop time at each station is about 30 seconds and by considering the time of accelerating and decelerating, t_{sb} is assumed as 1 minute (0.017 hour). Based on transportation literature, the amount of α_0 and α_1 (parameters in equations 6 and 7) are considered as 0.15 and 4 respectively, therefore:

$$t_{vc}^i(f_{c1}^i) = 0.0181(1 + 0.15(\frac{f_{c1}^i}{6000})^4) \tag{24}$$

$$t_{vb}^i(f_b) = 0.0510(1 + 0.15(\frac{f_b}{450})^4) + 0.017 \tag{25}$$

$$f_{c1}^{i}=\frac{\sum_{l=1}^{i}\sum_{j=i+1}^{12}D_{c}^{ij}}{1.34}=$$

$$=\frac{\sum_{l=1}^{i}\sum_{j=i+1}^{12}D^{ij}\frac{e^{01.52\times10^{-5}t_{vc}^{ij}-0.00306(110|j-i|+\tau_c)}}{e^{01.52\times10^{-5}t_{vc}^{ij}-0.00306(110|j-i|+\tau_c)}+e^{1.108-0.00655t_{vb}^{ij}-0.0342\tau_b}}}{1.34} \tag{26}$$

And finally:

$$t_{vc}^{ij}=|j-i|t_{vc}^{i}\left(f_{c1}^{i}\right) \tag{27}$$

$$t_{vb}^{ij}=|j-i|t_{vb}^{i}(f_b) \tag{28}$$

Distance matrix for this corridor (considering 817 meter as a distance of two consecutive sections) and parameters of this case study are summarized in Table 2 and Table 3 respectively.

Table 2. Distance matrix between sections of the case study corridor

X_c^{ij}	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	0	0.817	1.634	2.451	3.268	4.085	4.902	5.719	6.536	7.353	8.17	8.987
2	0.817	0	0.817	1.634	2.451	3.268	4.085	4.902	5.719	6.536	7.353	8.17
3	1.634	0.817	0	0.817	1.634	2.451	3.268	4.085	4.902	5.719	6.536	7.353
4	2.451	1.634	0.817	0	0.817	1.634	2.451	3.268	4.085	4.902	5.719	6.536
5	3.268	2.451	1.634	0.817	0	0.817	1.634	2.451	3.268	4.085	4.902	5.719
6	4.085	3.268	2.451	1.634	0.817	0	0.817	1.634	2.451	3.268	4.085	4.902
7	4.902	4.085	3.268	2.451	1.634	0.817	0	0.817	1.634	2.451	3.268	4.085
8	5.719	4.902	4.085	3.268	2.451	1.634	0.817	0	0.817	1.634	2.451	3.268
9	6.536	5.719	4.902	4.085	3.268	2.451	1.634	0.817	0	0.817	1.634	2.451
10	7.353	6.536	5.719	4.902	4.085	3.268	2.451	1.634	0.817	0	0.817	1.634
11	8.17	7.353	6.536	5.719	4.902	4.085	3.268	2.451	1.634	0.817	0	0.817
12	8.987	8.17	7.353	6.536	5.719	4.902	4.085	3.268	2.451	1.634	0.817	0

Thus, the objective functions are as follows:

$$\min AP=\left(\sum_{i=1}^{12}\sum_{j=i}^{12}\left[\frac{D_c^{ij}}{1.34}X_c^{ij}\right]+\sum_{i=1}^{12}\sum_{j=1}^{i}\left[\frac{D_c^{ij}}{1.34}X_c^{ij}\right]\right)\times0.135+19.6\times f_b\times0.598$$

$$=0.101\left(\sum_{i=1}^{12}\sum_{j=i}^{12}D_c^{ij}X_c^{ij}+\sum_{i=1}^{12}\sum_{j=1}^{i}D_c^{ij}X_c^{ij}\right)+11.72f_b \tag{29}$$

$$\max\ SW=\sum_{i}\sum_{j}\frac{D^{ij}}{0.00411}\ln(e^{U_c^{ij}}+e^{U_b^{ij}})+\sum_{i}\sum_{j}\frac{D_c^{ij}}{1.34}\tau_c+\sum_{i}\sum_{j}D_b^{ij}\tau_b-13211.7208\times f_b \tag{30}$$

5. Solution methods and computational results

As there is no analytical solution method due to high complexity of the proposed model, the proposed bi-objective constrained-optimization model with nonlinear objective functions are solved by using the numerical approach. Therefore, considering solution methods introduced in the literature to solve bi-objective constrained model (for example, Tirkolaee et al. 2019, Goli et al., 2019, Hajipour et al., 2014, Rahmati, Hajipour and Niaki, 2013), two meta-heuristic algorithms (NSGA-II, MOHS) are suggested to solve the model utilizing the data from the case study. NSGA is a usual method for solving multi-objective optimization which is based on Genetic Algorithms. NSGA-II was introduced to solve some of the NSGA's problems (such as deficiencies in choosing dominant particles, and its computational complexities).

The NSGA-II performs better than NSGA by utilizing the information of the population non-dominated population by solution P and the number of times solution P becomes non-dominated. By using the NSGA-II, a random parent population is produced (Each solution is a vector with three entities of (f_b , τ_b , τ_c) which is produced by using uniform distribution and satisfies the constraints). Then Non-dominated sorting will be performed for the population. A fitness value is assigned to each solution equal to its non-domination level. Then a child population will be created by using the binary tournament selection, recombination and mutation operators. After that, parent and child populations will be combined as a new population and non-dominated sorting will be performed for them. The new parent population will be formed by adding solutions from the first front up to the population size. Thereafter, the solutions of the last accepted front are sorted based on their non-domination rank and their crowding distance. The first points of this new sorted set will be used for binary tournament selection, one-point arithmetic crossover and mutation to create child population. This procedure continued up to reaching the defined maximum iteration (Deb et al. 2000).

Table 3. Parameters of the case study

Parameter	Value	Parameter	Value
P	12	Fu_c	0.598
$f_b^{\max}$	200	Fu_b	0.135
$f_b^{\min}$	60	τ_{Fu_c}	10000
O_r	1.34	τ_{Fu_b}	3000
k	90%	$P_{driver/h}$	660000
β_c	-0.00411	Ca_b	200

```
Input parameters (Initial population number, Maximum iteration, Crossover rate and mutation rate)
Generate random population –size N
Evaluate Objective Values
Assign Rank (level) Based on Pareto dominance - sort
Generate Child Population
  Binary Tournament Selection
  Recombination and Mutation
for i=1 to Max number of iteration do
    for each Parent and Child in Population do
        Assign Rank (level) Based on Pareto -sort
        Generate sets of non-dominated solution
        Loop (inside) by adding solutions to next generation starting from the first front until N
individuals found determine crowding distance between points on each front
    end for
    Select points (elitist) on the lower front (with lower rank) and are outside a crowding distance
    Create next generation
       Binary Tournament Selection
       Recombination and Mutation
end for
```

In MOHS algorithm (which is somehow a new meta-heuristic algorithm), each solution is called harmony and will be shown by a vector with n dimension. This algorithm has three main phases. First, an initial generation of harmony vectors (solutions) will be produced randomly and will be recorded in harmony memory. The number of harmony vectors will be equal to Harmony Memory Size (HMS).Then a new harmony vector will be produced from current solutions either by using the rules of harmony memory consideration rate (HMCR) and pitch adjustment rate (PAR) with probability of HMCR*(1-PAR[1])) and HMCR * PAR respectively or by random generation with probability of 1-HMCR. Then the rank of each harmony will be calculated. For this purpose, non-dominated harmony will have a rank equal to one and for dominated harmonies the rank will be equal to one plus number of harmonies of the current iteration which dominate that harmony. Finally, the harmony memory will be updated. The main difference of NSGA-II with MOHS is in their evolution process. In MOHS process evolution is performed using the single objective HS. However, GA is used as the NSGA-II process evolution and selection strategy in NSGA-II is the binary tournament (Ricart, et al. 2011).

[1] Pitch Adjustment Rate

Initialize Population
Generate random Harmony Memory (HM)
while stopping criteria (maximum number of iteration) is not satisfied **do**
  Improvise a new solution S
    for each variable s_i **do**
      if *U (0,1)* < HMCR **then**
        $s_i^{new} \leftarrow s_i^j$ where $j \leftarrow \text{int(U(0,1)*HMS)}+1$
        if *U (0.1)* < PAR **then**
          Update s_i^{new} with $s_i(k+m)$
        end if
      else
        $s_i^{new} \leftarrow \text{random value}$
    end for
  Calculate the Pareto ranking of S considering HM
    $rank(S, IN\text{=Iteration Number}) = 1 + p_s^{(IN)}$ where $p_s^{(IN)}$ denotes the number of solutions for the current iteration which dominate the solution in question
  if S has a better ranking than the worst solution in HM **then**
    Update HM with S
  end if
end while

Algorithms' parameters adjustment (tuning) had been done by Taguchi experiment design method. Results for MOHS and NSGA-II are summarized in table 4 and Table 5 respectively.

Table 4. Computational results of parameter tuning for NSGA-II by Taguchi method

Run number	Algorithm Parameters				Response MOCV
	nPop	P_C	P_m	Max IT	
1	1	1	1	1	2.292E-6
2	1	2	2	2	2.793E-6
3	1	3	3	3	2.759E-6
4	2	1	2	3	2.762E-6
5	2	2	3	1	2.580E-6
6	2	3	1	2	2.720E-6
7	3	1	3	2	2.769E-6
8	3	2	1	3	2.753E-6
9	3	3	2	1	2.780E-6

For NSGA-II and MOHS algorithms, following parameters are adjusted respectively:

- Initial population number, Maximum iteration, Crossover and mutation rates
- Harmony memory size, Maximum iteration, Harmony memory consideration rate, Pitch adjustment rate and Bandwidth rate

For each factor three levels were considered (low, medium, high). By using Minitab software, the L9 design and the L27 design were used for NSGA-II and MOHS algorithms respectively. The metric introduced by Tavakkoli-Moghaddam, et al. (2016) is called Multi-objective coefficient of variation (MOCV), and is defined by dividing the MID metric by the DIVERSITY metric, was used as the response of Taguchi method for each algorithm.

Table 5. Computational results of parameter tuning for MOHS by Taguchi method

Run number	Algorithm Parameters					Response MOCV
	HMS	Max IT	PAR	HMCR	BW	
1	1	1	1	1	1	3.11E-6
2	1	1	1	1	2	2.03E-6
3	1	1	1	1	3	1.97E-6
4	1	2	2	2	1	2.57E-6
5	1	2	2	2	2	1.94E-7
6	1	2	2	2	3	1.57E-7
7	1	3	3	3	1	2.51E-6
8	1	3	3	3	2	6.06E-7
9	1	3	3	3	3	5.45E-8
10	2	1	2	3	1	1.11E-7
11	2	1	2	3	2	9.61E-6
12	2	1	2	3	3	7.54E-7
13	2	2	3	1	1	4.73E-7
14	2	2	3	1	2	4.46E-7
15	2	2	3	1	3	2.75E-6
16	2	3	1	2	1	2.21E-6
17	2	3	1	2	2	3.54E-7
18	2	3	1	2	3	2.52E-6
19	3	1	3	2	1	1.97E-6
20	3	1	3	2	2	3.56E-7
21	3	1	3	2	3	2.04E-6
22	3	2	1	3	1	2.94E-7
23	3	2	1	3	2	8.19E-7
24	3	2	1	3	3	2.57E-6
25	3	3	2	1	1	2.55E-6
26	3	3	2	1	2	2.52E-6
27	3	3	2	1	3	4.29E-7

In MOCV both metrics (distance from ideal solution and its diversity) were combined, therefore, convergence and diversity of Pareto solution is considered simultaneously. Using the MOCV metric resulted in more precise Taguchi parameter adjustment.

Due to Taguchi results (Figure 3) and due to maximizing the noise to signal ratio, optimal level of all factors in NSGA-II is level one (low) and in MOHS factors is level one (low) for HMS, level two (medium) for max iteration and level three (high) for other parameters. Table 6 summarizes the optimal amount of all parameters resulting of Taguchi method.

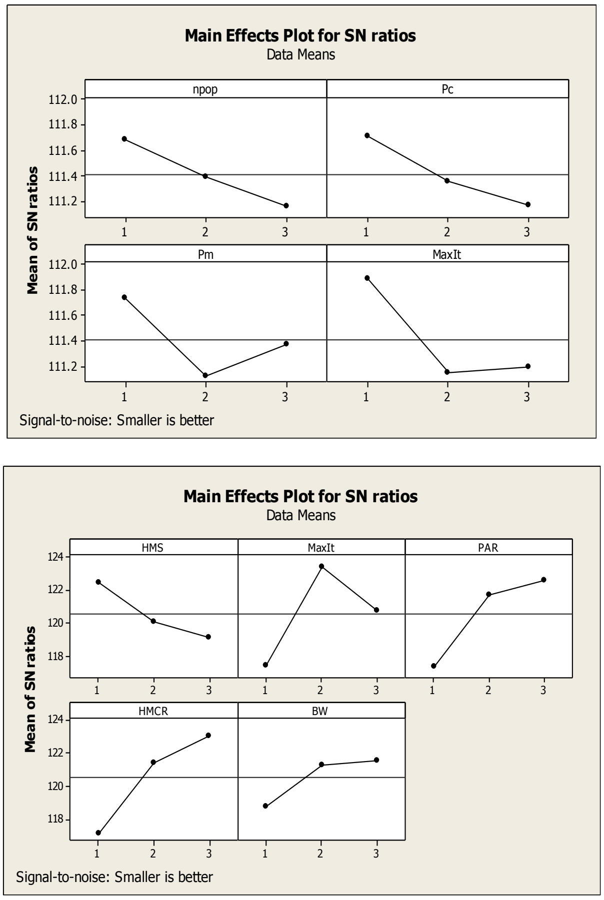

Figure 3. Taguchi results for NSGA-II (up) and for MOHS (down)

Table 6. Algorithms parameters and their levels in Taguchi method

NSGA-II Algorithm					
Parameter	**Parameter Range**	**Low (1)**	**Medium(2)**	**High(3)**	**Taguchi result**
nPop	30-100	30	50	100	30
P_C	0.6-0.9	0.6	0.8	0.9	0.6
P_m	0.2-0.4	0.2	0.3	0.4	0.2
MaxIT	50-200	50	100	200	50
MOHS Algorithm					
HMS	30-100	30	70	100	30
HMCR	0.6-0.9	0.6	0.75	0.9	0.9
PAR	0.2-0.9	0.2	0.4	0.9	0.9
Bandwidth (BW)	2-4	2	3	4	4
MaxIT	30-100	30	50	100	50

For comparison of both algorithms, ten test problems based on different amount of p were designed. Demand matrix for test problems produced randomly by the Matlab software. Without loss of generality, distance matrix was expanded the same as the case study distance matrix. Average amount of performance metrics which are introduced in Schott (1995) are calculated for ten times test problems' run and summarized in Table 7.

Table 7. Average value of algorithm performance evaluation metrics of test problems

Test Problem	NSGA-II					MOHS				
	TIME	NOP	DIVERSITY	SPACING	MID	TIME	NOP	DIVERSITY	SPACING	MID
1(P=5)	2.47	90	1480570	1.22040	4.940	3.834	22	1019059	1.8973	31.950
2(P=10)	3.03	100	1293566	0.68830	4.270	4.210	42	3727702	1.9100	1.6433
3(P=15)	2.43	100	2111695	0.76130	9.512	4.290	40	3841469	1.3908	4.8363
4(P=20)	3.63	100	3964835	0.86457	10.68	6.594	56	2674966	1.0148	15.719
5(P=25)	5.52	100	5456603	0.78360	11.80	6.641	40	3665885	1.3320	18.249
6(P=30)	9.98	90	88213031	1.84090	1.185	7.486	13	3663182	1.7860	26.850
7(P=35)	23.37	100	6445844	0.98720	22.16	9.114	24	4919247	1.6902	28.656
8(P=40)	89.38	100	4834308	0.87003	38.87	13.69	22	5492932	1.7700	33.701
9(P=45)	248.40	81	12647227	0.83847	18.987	19.137	15	5581197	1.5360	43.330
10(P=50)	1158.1	74	14496686	1.25000	20.60	29.729	14	138273663	1.8322	2.4320

By one-way ANOVA for 95% confidence interval, performance metrics of two algorithms were examined. The results (summarized in Table 8) show that both algorithms have significant difference in number of Pareto solution and spacing metric but other metrics show no significance differences.

Table 8. ANOVA results

Metric	Source	DF	SS	MS	F	P
Run time	Algorithms	1	103916	103916	1.59	0.223
	Error	18	1173206	65178		
	Total	19	1277122			
NO. of Pareto solution	Algorithms	1	20930	20930	136.8	0.000
	Error	18	2754	153		
	Total	19	23685			
Diversity	Algorithms	1	5.09282E+13	5.09282E+13	0.04	0.843
	Error	18	2.25646E+16	1.25359E+15		
	Total	19	2.26156E+16			
MID	Algorithms	1	207	207	1.23	0.281
	Error	18	3018	168		
	Total	19	3225			
Spacing	Algorithms	1	1.833	1.833	17.84	0.001
	Error	18	1.849	0.103		
	Total	19	3.682			

According to Table 7, it is obvious that number of Pareto solution (which will be better if the amount be higher) in NSGA-II is better than MOHS. Regarding spacing metrics (which will be better if the amount is lower) except test problem 6, spacing metric is better in NSGA-II than MOHS. It can be concluded that for this problem, NSGA-II has better performance than MOHS.

6. Managerial insights

Regarding the results achieved by analyzing the case study, bus fees are not more than 50 Rials in all solutions. The low amount of fee can be interpreted as a suggestion to make the public transportation free. The results support the theory that decreasing fee as much as possible (up to making it free) will be an incentive for passengers to use public transportation. Therefore, public transportation demand increases while the private car usage decreases (assuming constant total demand). Decreasing bus fare, may be compensated by an increase in its demand. Meanwhile air pollution will be decreased due to decreasing private car demand. Therefore, the transportation system managers (government) may support free public transport (public transport subside) based on the case study.

It is worth mentioning that lower bus fare in Pareto solutions will increase the bus demand, and if suitable increase does not happen in the bus frequency, it will lead to a crowded situation inside the bus and passengers' dissatisfaction. But it is better to improve the model by considering the crowding inside the bus in its utility function.

Average bus frequency of Pareto solutions lies between 60 and 65. At the time of study, the real bus frequency in this corridor was 70 which is a little more than the results. If we change the $f_b^{\min}$ to be between 0 and 60 (it means that we consider a situation in which model can suggest us to have no public transportation), the average bus frequency will be between 53 to 58. If we increase $f_b^{\max}$ to the maximum corridor bus capacity (450 buses), (assume that there is no limitation to provide enough number of bus), the average bus frequency will be between 60 and 70.

Average private car toll in different runs were less than 10000 Rials (half of the higher bound of the model). But solutions diversity was high. Increasing higher bound to 1 million Rials (50 times greater) do not increase average car toll in Pareto solution to more than 150000 Rials (15 times greater).

7. Conclusion

In this paper, as an overall picture, a bi-objective optimization model is proposed in which the transportation prices were determined in a way to maximize social welfare and minimize relative air pollution simultaneously. A numerical approach was required for solving this model, therefore, the model was solved by using two meta-heuristic algorithms (NSGA-II, MOHS). Then, the comparison of these algorithms was done by using one-way ANOVA for performance metrics. The comparison shows that the performance of NSGA-II for the test problems is significantly better than MOHS in terms of some metrics (number of Pareto solutions and spacing).

The main contributions of this model can be summarized as the following:

1. It tries to fill the existing gap in the rare optimization model used in designing transport pricing schemes.
2. It formulates a pricing problem mathematically and uses the data from a case study for solving the model numerically.
3. It considers improving transport sustainability by using the minimization of air pollution as one of the objective functions while improving social welfare.
4. It determines optimal prices (bus fare and car toll) and optimal designing factor (bus frequency) simultaneously in an integrated model.

From the economical point of view, the obtained results showed that free public transport is an effective solution for decreasing air pollution while determining the bus frequency and car toll in such a way that the social welfare will be maximize.

Solving the model using other new meta-heuristic algorithms and comparing their results with the results of this paper is recommended. Expanding the model by incorporating subway mode in the model can be useful. Extending the model to the network level, inserting decision variable of fuel price and considering the rate of crowding inside of the public transportation in utility function can help to achieve more realistic model with more precise results in real world.

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