PREDICTIVE CORDON PRICING TO REDUCE AIR POLLUTION[1]

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1 Introduction

In recent years, air pollution has become a serious environmental problem, particularly in large cities. According to a World Health Organization (WHO) report [1], seven million premature deaths worldwide that were related to air pollution occurred in 2012. Indeed, one in eight global deaths is a result of air pollution exposure. Traffic congestion is one of the main sources of air pollution in large cities. The US Environmental Protection Agency (EPA) notes that transportation is responsible for more than 75 percent of CO emissions [2] and 55 percent of NOx emissions [23]. Hence, controlling and reducing emission in the transportation sector is a priority for tackling air pollution.

Experience in London, Milan, and Stockholm shows that charging for the use of roads can be effective in reducing emissions as well as congestion [4,5]. Moreover, several theoretical studies have investigated the potential of network pricing to reduce pollution. These studies include link-based tolls [6,7,8] and cordon tolls [9,10]. There is also an extensive literature in atmospheric science on the determination of optimal tolls to reduce human exposure to pollution [11,12]. Establishing a relationship between ambient air pollution, weather forecasts and pricing will make tolling more efficient. However, to the best of our knowledge, there has been no research on tolling vehicles with different emissions characteristics when tolls are updated based on meteorological considerations.

The main goal of this paper is to apply predictive daily tolls for different classes of vehicles in order to decrease air pollution. The next section defines the problem, and Section 3 formulates the mathematical model. Section 4 presents a numerical example showing how tolling leads to an increase in the share of trips made by public transit, thereby contributing to a reduction in total network emissions and improved air quality. Section 5 concludes.

2 Problem definition

This paper is an attempt to coordinate toll policy with meteorological parameters to impose less cost to the citizens while pricing transportation congestion and environmental externality. It follows Poorzahedy et al., 2016, [13] which determined optimal tolls for next days based on historical weather data to reduce air pollution in a large city, Shiraz, Iran. The present study, besides traffic characteristics, considers weather forecast and ambient air pollution to specify day-to-day optimal toll for different classes of vehicles. Vehicles are divided into three classes according to their emission characteristics, and higher tolls are imposed on more polluting vehicles. Since measuring the exact amount of emissions from each vehicle is not practical, vehicles are classified according to characteristics related to emissions such as age, fuel type, and European emission standard.

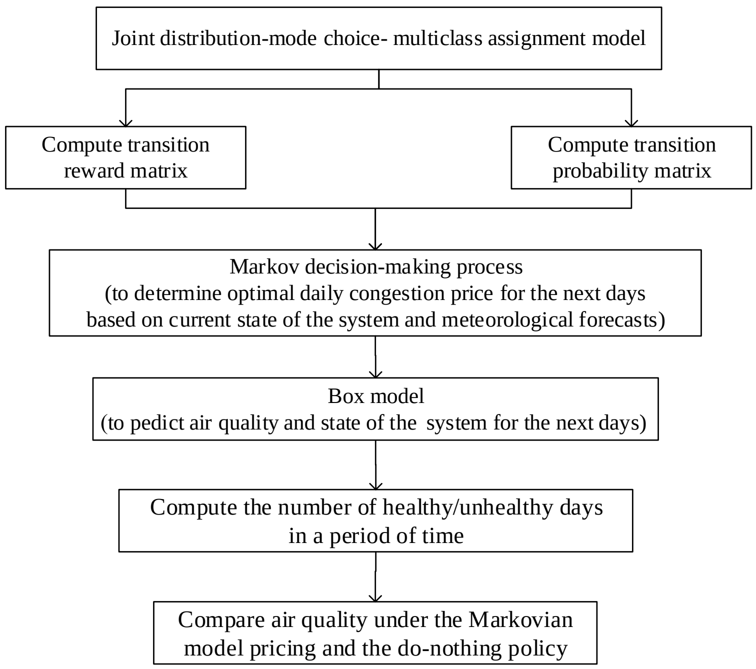
A joint distribution-mode choice-multiclass assignment model is applied to simulate traffic condition under each pricing policy. In this model, travelers choose their destination inside or outside the cordon, and whether to drive or take public transit. Imposing a toll encourages travelers to take public transit or use less-polluting vehicles. Thus, it leads to less emissions and better air quality.

Probability and reward of moving from one state of the system (air quality) to another one are calculated by the outputs of assignment problem including speed, vehicle-kilometers, auto/transit demand, and auto travel time. A Markov decision-making process then determines daily toll levels with the objective of maximizing welfare measured by traveler utility, transportation cost, and air pollution health costs. Setting

[1] 54th Annual Meetings of the *Canadian Transportation Research Forum*, May 26 - 29, 2019 at Vancouver, British Columbia

the toll as a function of current pollution levels and forecast weather conditions refers to responsive tolls. In order to compare air quality under responsive tolls with the do-nothing strategy, a Box model is used. This model predicts air quality. For simplicity, air quality is categorized into three intervals called “Healthy” (air quality index (AQI <100), “Unhealthy” (100<AQI<200), and “Dangerous” (AQI>200). Winds are also divided into three speed-based categories called “low effect”, “medium effect”, and “high effect” winds. Figure 1 shows the different steps of the problem which are formally explained in the next section.

Figure 1: An overview of the decision problem



3 The problem formulation

3-1 Assignment problem

As a result of the pricing policy, people may change their destination (inside or outside the cordon) and/or their mode of transportation. Hence, we use a joint distribution-modal split multiclass assignment problem (*P1*) [14] in which destination choice, route choice, and mode choice (between car and bus) are present in the first, second and third terms, respectively. The constraints include flow and demand conservation for each class, non-negative flows, and link trips’ expression.

$$(P1) \quad Min\Big(\sum_{a\in A}\int_0^{x_a} t_a(u)du + \sum_{a\in A}\sum_{m\in M}\frac{1}{\beta^m}x_a^m\tau_a^m + \sum_{(k,s)\in W}\sum_{m\in M}\int_0^{\hat{x}^{ks,m}}\Big(\frac{1}{\theta^m}Ln\frac{z}{x^{ks,m}-z}+\hat{t}^{ks}\Big)dz$$

$$+\sum_{m\in M}\sum_{(k,s)\in W}\frac{1}{\eta^m}\big(x^{ks,m}.Lnx^{ks,m}-x^{ks,m}\big)\Big)$$

where m: Class of user's vehicle, $m=1, \ldots, M$,

a: A link of the network, $a\in A$,

(k,s): An O/D pair, $(k,s)\in W$,

x_a: Total auto flow in link a,

x_a^m: Auto flow of class m in link a,

$\hat{x}^{ks,m}$: Public transit demand (passenger) between k and s shifted from class m,

$x^{ks,m}$: Demand (passenger) of auto vehicle class m between k and s,

τ_a^m: Toll to be paid by class m for entering to link a,

β^m: The value of time (VOT) for class m, $\beta^m > 0$,
θ^m: Logit parameter for choosing a mode of transportation by users of class m,
η^m: Logit parameter for choosing a destination by users of class m,
$t_a(.)$: Travel time on link a, and
$\hat{t}^{ks}$: Public transit travel time between k and s.

3-2 Markov decision-making model

Markov model is a type of stochastic decision-making model which is used when the results are probabilistic. Let i be the current state of the system and N be the number of stages for making decisions (let say days). A finite stage Markov process makes decisions in the way that maximizes expected outcomes of transition from state i to j under the decision $q \in Q$ throughout all stages. Q is an arbitrary decision set. A recursive algorithm introduced by Howard [15] is used to find the optimal decision. Problem ($P2$) denotes Markov process objective function:

$$(P2)\ f_{n-1}(i) = \max_q \{V_i^q + \sum_{j=1}^{J} p_{ij}^q . f_n(i)\} \qquad n=N, N-1, ..., 2$$

where $f_{n-1}(i)$ is Expected optimal outcome from stage $n-1$ and on when the state of the system is i at stage n. q is a decision; in this study, q is defined as pricing policy, $q = (\tau^{m=1}, \tau^2, \tau^3)$). v_i^q is expected outcome in each transition under decision q and $v_i^q = \sum_{j=1}^{J} p_{ij}^q . r_{ij}^q$; (p_{ij}^q) and (r_{ij}^q) are Probability and Reward matrices under decision q.

3-2-1 The transition Reward matrix

The reward of a decision (q) includes three types of benefit/cost under that decision:

1- Health cost of unhealthy and dangerous air quality, C_j.
2- Traffic-related cost (independent of changing the state of the system), T^q, including auto operating cost, auto fuel cost, auto/transit passengers' cost of time and auto passengers' surplus.

The total reward of the system transition from state i to j when the operator makes the decision q is the sum of these two components. To find out monetizing traffic-related components, the reader is referred to Poorzahedy et al. (2016). VSL (Value of Statistical Life) method is also used to compute the monetary cost of air pollution. VSL is defined as aggregating individuals' willingness to pay (WTP) for a marginal reduction in the risk of premature death [16]. There is no standard method for measuring the cost of diseases caused by air pollution. These costs reduce the quality of life without reducing life expectancy such as ambulance costs, purchasing medicines, loss of leisure time, and discomfort and anxiety linked to the illness. Some studies [17,18] have shown that roughly 10 percent of the cost of mortality is a good estimate for the cost of illness.

3-2-2 The transition Probability matrix

The transitions from one state of the system to another are caused by the combined influence of three factors: 1) ambient air pollution, 2) emissions due to traffic, and 3) meteorological parameters [13]. Let $\tilde{p}(i,j)$ denote the probability of transition from state i (today) to state j (tomorrow) in stationary conditions (unchanging weather); $w_{v,ij}$ represents the probability of changing state i to j by wind type v (1: low effect, 2: medium effect, 3: high effect) and $p^s(\gamma_l \mid I_k)$ shows the occurrence probability of wind γ_l ($l=1,2,3$) in season s when wind I_k ($k=1,2,3$) is forecasted. $\tilde{p}(i,j)$ can be obtained by the exponential distribution function used wildly for estimating the lifetime (see [13])

Given I_k, the probability of transition from i (today) to j (tomorrow) in season s, $P^s(i,j)$, can be obtained by combining $\tilde{p}(i,j)$, $w_{v,ij}$, and $p^s(\gamma_l \mid I_k)$. For instance, the following equations illustrate the probability of going from healthy state (i=1) to other states:

$$P^s(1,1) = \tilde{p}(1,1) + \tilde{p}(1,2). \sum_{j=1}^{3} p^s(\gamma_l|I_k). w^s_{j,21} + \tilde{p}(1,3). \sum_{j=1}^{3} p^s(\gamma_l|I_k). w^s_{j,31}$$

$$P^s(1,2) = \tilde{p}(1,2). \sum_{j=1}^{3} p^s(\gamma_l|I_k). w^s_{j,22} + \tilde{p}(1,3). \sum_{j=1}^{3} p^s(\gamma_l|I_k). w^s_{j,32}$$

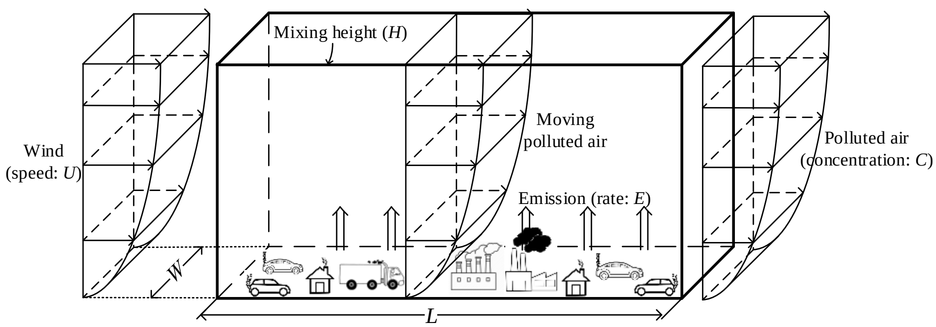
$$P^s(1,3) = \tilde{p}(1,3). \sum_{j=1}^{3} p^s(\gamma_l|I_k). w^s_{j,33}$$

3-3 Air quality prediction

To compare the air quality under Markov decisions (responsive tolls) with other alternatives (do-nothing and flat tolls which means the same toll from day to day), pollutant concentration should be estimated for next days. This comparison demonstrates how efficient the policies are. Hence, Box model, a simple pollution dispersion model, is applied to approximate pollutant concentration based on wind, background concentration and traffic flow [19].

This model defines the atmospheric volume around a city by a rectangular area extending to the mixing height, *H*, as shown in Figure 2. Pollutants emitted into the box at a constant rate *E* (pollutant weight per unit time) are assumed to be mixed instantaneously with the air inside the box. Wind is assumed to enter the box at a speed *U*, and polluted air with the same concentration as the interior of the box is assumed to exit from the opposite side which is the only direction of pollutant dispersion [20].

Figure 2: Box model details



The pollutant concentration on day *d* inside the box (pollutant weight per unit volume) may be written as:

$$\bar{C}_d = \frac{\bar{E}_d + V . \bar{C}_{d-1}}{W . H . (L + \bar{U}_d)}$$

where $\bar{C}_d$ (or $\bar{C}_{d-1}$) is average hourly pollutant concentration on day *d* (or *d*-1),

$\bar{E}_d$ is average hourly emission rate in day *d*,

$\bar{U}_d$ is average hourly wind speed in day *d*,

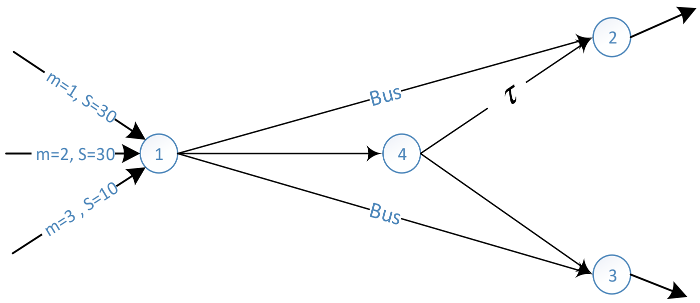
W, *L*, and *H* are box dimensions perpendicular to the wind direction, parallel with wind direction and height of the box, respectively, and

V is the volume of the box equals to *W.L.H*.

4 A numerical example

In this study, a hypothetical network is provided to demonstrate the proposed models and solution framework. As shown in Figure3, this network contains one origin and two destinations. Vehicles are categorized as buses and automobiles, and automobiles are divided into three classes with different emission characteristics. Buses travel on exclusive traffic lanes, and bus travel time is independent of traffic flow. This example does not feature route choice since automobiles and buses alike have only one route to a given destination. Volume-Delay Functions for automobiles are assumed to have the Bureau of Public Roads form $t_{ij}(x_{ij})=t_{ij}^0+a_{ij}.\ x_{ij}^4$ and destination 2 is considered as a congested and polluted area which its entrance link (4,2) should be tolled.

Figure 3: Example network and demand for different classes of vehicles



4-1 Multiclass assignment model

To solve the problem (*P1*), different parameters are required. These parameters are listed in Table 1 and 2. The decision set is designed in the way that tolls have harmony with travelers' value of time and the travel time on the tolled link as well.

Table 1: Volume-Delay Function parameters ($t_{ij}(x_{ij})=t_{ij}^0+a_{ij}.\ x_{ij}^4$)

Link(i,j)	t_{ij}^0 *(min)*	a_{ij} *(min/vehicle⁴)*
(1,4)	3	$9*10^{-7}$
(4,2)	5	$1.5*10^{-5}$
(4,3)	7	$1*10^{-5}$

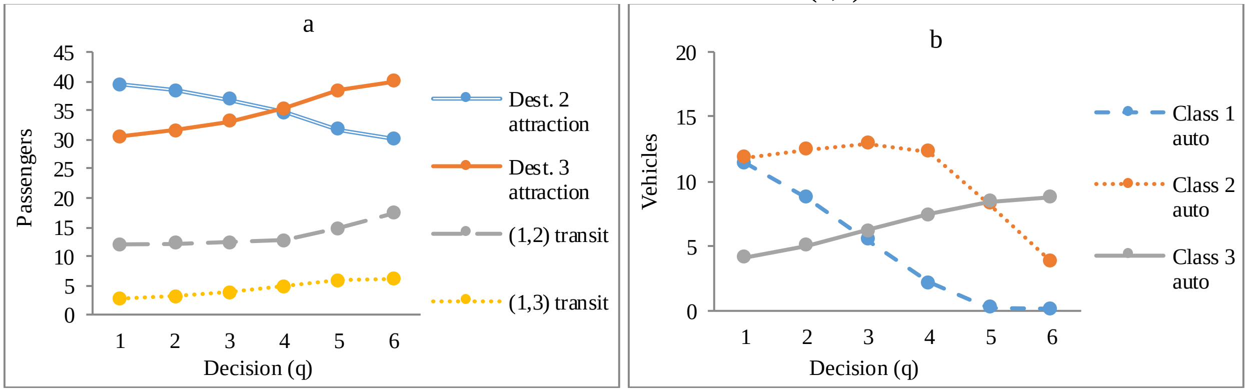
Table 2: Assignment model parameters for different classes

Class (m)	$S^{k,m}$ *(passenger)*	β^m *(Toman*/min)*	θ^m *(1/min)*	η^m	τ^m*(Toman/vehicle)*					
					q=1	*q=2*	*q=3*	*q=4*	*q=5*	*q=6*
1	30	*210*	0.1	0.2	0	1000	2,500	5,000	10,000	15000
2	30	*415*	0.2	0.2	0	600	1,500	3,000	6,000	9000
3	10	*830*	0.3	0.2	0	200	500	1,000	2,000	3000

* *Toman* is the currency of Iran (1 USD = 4200 Toman)

Results of (*P1*) indicate that as the toll increases, the number of trips to destination 2 decreases while trips to destination 3 gradually increase as illustrated in Figure 4 (a). Figure 4 (b) shows the flow of each class in the link with tolls. As the toll increases, flows of class 1 and 2 (old and polluting cars) reduce while the flow of class 3 (hybrid or green cars) increases due to less toll for this class and less traffic in the tolled link.

Figure 4: a) Total trips to each destination and share of public transit under different toll levels; b) Traffic flow of each class in the tolled link (4,2)



4-2 Markov decision-making process

For a one-week weather forecast package, Markov decision- making process results are shown in Table 3 which maximize rewards over one week. If air quality is healthy on Day 1, the planner will choose $q=5$ (see Table 2). If air quality is unhealthy or dangerous, the planner will select $q=6$. In next days, forecasting wind type 2 leads to a significant drop in optimal toll.

Table 3: Markov model results for a seven-day weather forecast packet

Day	Date	Predicted wind type	Markov decision vector
1	2016.10.27	1	(5,6,6)
2	2016.10.28	2	(1,4,6)
3	2016.10.29	2	(1,5,6)
4	2016.10.30	2	(3,5,6)
5	2016.10.31	1	(5,6,6)
6	2016.11.01	1	(3,5,6)
7	2016.11.02	1	(1,1,6)

*Forecasted winds refer to Tehran, capital of Iran.

We can make the results more accurate by using updated forecast package which is rolling. Hence, we can take the first day decision and for the second day use another one-week forecast package.

4-3 Using Box model to predict the air quality for the next day

In this study, CO is selected as the pollutant since vehicles are responsible for almost all CO emissions. Previous research has shown that CO emissions can be approximated well using a function based on average speed. We use an equation that links average speed (V) to CO emission (E_{CO}) that was developed for Iran [21]:

$$E_{CO} = 127.64 - 2.68V + 0.016*V^2 + 160.12/V$$

Based on the AQI breakpoints introduced by EPA, the CO concentration on the boundary between healthy and unhealthy conditions (AQI=100) is equal to 9.5 ppm (11685 kg/km^3) and for the boundary between unhealthy and dangerous conditions (AQI=200) is 15.5 ppm (19065 kg/km^3).

4-4 Compare air quality under responsive tolls and do-nothing policy

In this section, Markov decisions are compared to do-nothing alternative and a flat toll scenario during the simulation period. For this purpose, we assumed in the day before starting the simulation, air quality is "healthy" and CO concentration is 5000 kg/km^3. So, $q=5$ is selected for the first day based on Markov results. Then, CO emission rate (E) under this decision is calculated and Box model computes CO

concentration according to the background concentration and wind speed on that day. The results are shown in Table 4.
The results indicate that compared to do-nothing, with responsive tolls the number of days with dangerous air quality is reduced from five to one, while the number of days with healthy air quality rises from two to six. Also, responsive tolls reduce daily average *CO* concentration by 19.6 percent over a 22-day simulation period. Although the highest flat toll leads to one more healthy day and more reduction in *CO* concentration, it has higher traffic-related cost and achieves a slightly lower benefit than the responsive toll. The potential welfare gain from each policy is inexact because the toll for each vehicle class is restricted to a discrete set of six alternatives; so it worth mentioning here that, for other case studies, the benefit of responsive tolls would be much higher or even lower than flat tolls. Further studies are required to clarify this issue.

Table 4: comparison of air quality under Markov decisions and do-nothing alternative

Date	Daily Average Wind Speed *(km/hr)*	*Responsive tolls*				*Do nothing*		*Flat toll*	
		Markov Decision-making Model				*q*=1		*q*=6	
		Decision vector	Decision Made (*q*)	*CO* Concentration *(1000kg/km³)*	Air Quality	*CO* Concentration *(1000kg/km³)*	Air Quality	*CO* Concentration *(1000kg/km³)*	Air Quality
2016.10.21	-	-	-	5.00	Healthy (observed)	5.00	Healthy (observed)	5.00	Healthy (observed)
2016.10.22	5.8*	(5,6,6)	5	7.54	Healthy	8.35	Healthy	7.3674E+03	Healthy
2016.10.23	5.4	(5,6,6)	5	9.81	Healthy	11.33	Healthy	9.4840E+03	Healthy
2016.10.24	5.8	(5,6,6)	5	11.67	Healthy	13.78	Unhealthy	1.1218E+04	Healthy
2016.10.25	11.5	(5,6,6)	5	11.62	Healthy	13.92	Unhealthy	1.1133E+04	Healthy
2016.10.26	10.1	(5,6,6)	5	11.96	Unhealthy	14.48	Unhealthy	1.1423E+04	Healthy
2016.10.27	4.0	(5,6,6)	6	13.96	Unhealthy	17.25	Unhealthy	1.3478E+04	Unhealthy
2016.10.28	5.8	(1,3,6)	3	15.74	Unhealthy	18.87	Unhealthy	1.4647E+04	Unhealthy
2016.10.29	7.6	(5,6,6)	6	15.89	Unhealthy	19.40	Dangerous	1.4989E+04	Unhealthy
2016.10.30	7.2	(1,1,6)	1	17.10	Unhealthy	20.01	Dangerous	1.5401E+04	Unhealthy
2016.10.31	16.2	(5,6,6)	6	14.13	Unhealthy	16.91	Unhealthy	1.2975E+04	Unhealthy
2016.11.01	10.4	(5,6,6)	6	13.64	Unhealthy	16.66	Unhealthy	1.2751E+04	Unhealthy
2016.11.02	18.0	(5,6,6)	5	11.51	Healthy	14.12	Unhealthy	1.0785E+04	Healthy
2016.11.03	14.8	(6,6,6)	6	10.61	Healthy	13.26	Unhealthy	1.0104E+04	Healthy
2016.11.04	5.8	(6,6,6)	6	12.19	Unhealthy	15.44	Unhealthy	1.1750E+04	Unhealthy
2016.11.05	7.9	(6,6,6)	6	12.86	Unhealthy	16.44	Unhealthy	1.2501E+04	Unhealthy
2016.11.06	10.1	(6,6,6)	6	12.76	Unhealthy	16.43	Unhealthy	1.2485E+04	Unhealthy
2016.11.07	10.8	(6,6,6)	6	12.49	Unhealthy	16.17	Unhealthy	1.2277E+04	Unhealthy
2016.11.08	6.5	(6,6,6)	6	13.56	Unhealthy	17.63	Unhealthy	1.3379E+04	Unhealthy
2016.11.09	6.8	(5,6,6)	6	14.34	Unhealthy	18.70	Unhealthy	1.4187E+04	Unhealthy
2016.11.10	3.6	(6,6,6)	6	16.24	Unhealthy	21.24	Dangerous	1.6110E+04	Unhealthy
2016.11.11	3.6	(6,6,6)	6	17.98	Unhealthy	23.54	Dangerous	1.7853E+04	Unhealthy
2016.11.12	1.8	(6,6,6)	6	20.50	Dangerous	26.88	Dangerous	2.0385E+04	Dangerous
No. Healthy					**6**		**2**		**7**
No. Unhealthy					**15**		**15**		**14**
No. Dangerous					**1**		**5**		**1**
Ave. *CO* concentration				**1.3550E+04** (-19.6 %)		**1.6856E+04** (0)		**1.3031E+04** (-22.7 %)	
Health Cost**					**-120.81*** **		**0**		**-128.09**
Transp. Cost					**44.52**		**0**		**55.30**
Total Cost					**-76.30**		**0**		**-72.79**

* Daily Average of real wind speed in Tehran measuring every hour.
**Unit of the cost is Million Toman.
*** Negative costs represent benefit.

5 Conclusion

Traffic is a major contributor to emissions in many large cities with severe air pollution. Network pricing is widely believed to be a potentially effective method to manage transportation demand and control emissions. In this study, tolls are implemented for three classes of private vehicles with more polluting vehicles paying higher tolls. Optimal decision is chosen by a Markov decision-process according to ambient air pollution and weather forecast for the next seven days.
A numerical example demonstrates the proposed models and solution framework. Markov day-to-day tolls (responsive tolls) are compared to the do-nothing alternative and a flat toll scenario. Reductions in emissions and increases in the number of healthy days illustrate the efficacy of the models. With base-case parameters, responsive tolls reduce daily average *CO* concentration by 19.6 percent over a 22-day

simulation period. Compared to do-nothing, responsive tolls lead to four more healthy days and four less dangerous days. The results also indicate that responsive tolls cause lower total cost (higher welfare) in comparison with do-nothing and the highest level of flat tolls as well.
According to the results, high winds improve air quality. Thus, when the number of healthy and unhealthy days (before reaching to the dangerous condition) extend by imposing responsive tolls, and it becomes equal to the period of high-effect winds that make the air clean, the system (city) will be coordinated with nature and becomes stable. This means that the system can handle the air pollution problem.

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