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AIMS OF THE REVIEW

The main aim of the Review is to bring together the research work being done in the field of Transport Economics and arrange it organically in the form of a synthesis between theory and fact.

The situation facing transport economics is one in which old problems remain to be solved and new ones have been created by a wider range of information and improved methods of analysis. In addition, foreseeable development in the internal logic of theories and the formulation of fresh hypotheses to interpret complex phenomena, both economic and non-economic, are becoming the object of further research for which the Review is intended to be a medium of expression and comparison.

It is important in this respect to stress the fact that transport economics is prepared to take advantage of contributions from allied sciences and combine them in providing a more convincing interpretation of realities together with solutions to concrete problems. Within this framework the contributions to the Review from inside and outside Italy, though differing in standpoint and cultural background, will all be expected to maintain a rigorous standard of scientific scholarship.

RIVISTA INTERNAZIONALE DI ECONOMIA DEI TRASPORTI

FINALITÀ DELLA RIVISTA

 Questa Rivista si propone come scopo principale quello di contribuire all’opera di organica sistemazione delle ricerche nell’ambito dell’economia dei trasporti attraverso l’instaurazione di un processo di osmosi tra struttura teorica e fenomeni concreti. La realtà che tale disciplina ha dinanzi a sé, rappresentata dalla problematica irrisolta e da quella generata dall’affinamento dell’analisi e dell’informazione, e le prospettive che si dischiudono da uno sviluppo della logica interna delle teorie e della formulazione di nuove ipotesi interpretative di fenomeni di natura complessa, economici e non economici, costituiscono nel loro insieme il contenuto delle nuove ricerche per le quali la Rivista intende fornire un mezzo di espressione e di confronto.

In questa prospettiva finalistica, nella quale la stessa disciplina dell’Economia dei Trasporti si trova disposta ad arricchirsi del contributo di altre scienze e ad unirsi ad esse per una migliore interpretazione della realtà e per la risoluzione dei problemi concreti, si avvicenderanno i contributi nazionali ed internazionali che, pur diversi per approccio ed estrazione culturale, soddisferanno tutti la norma della credibilità scientifica.

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INCORPORATING VARIABLE TOLL RATES IN TRANSPORTATION PLANNING MODELS*

MARK W. BURRIS**

ABSTRACT: As transportation planning agencies look for cost-effective means to alleviate traffic congestion, one method is rarely investigated – variable tolls. Tolls that vary by time of day can be an effective demand management tool. One reason variable tolls are seldom used in practice is that planners cannot simply incorporate the variable toll rates into the models used to develop transportation alternatives. This research examined some of the factors involved in adding variable tolls to a transportation planning model and constructed a basic version of the variable tolling portion of that model. This basic model was then used to examine how a simple peak and off-peak variable toll rate might impact traffic flow. Not surprisingly, the variable toll reduced the peaking of traffic and reduced the total congestion and delay experienced by travelers. Improving transportation planning models in this manner would allow planners to compare these model results to results of other traffic congestion reduction options and select the right mix of strategies for their area.

JEL Classification: L91.

INTRODUCTION

Congestion pricing, or pricing travel at its marginal social cost, has long been advocated by economists as an efficient solution to the problem of traffic congestion (Pigou, 1920; Walters, 1968; Hau, 1992; DeCorla-Souza and Kane, 1992; Arnett and Small, 1994). Although theoretically attractive it is nearly impossible from a technical standpoint to accomplish marginal cost pricing on a real-time basis. Due to technical challenges and political objections, early forays into congestion pricing have focused on sub-optimal pricing schemes. The operational pricing scheme which most closely resembles marginal cost pricing is located in southern California on I-15. Toll level on this two-lane, reversible, high occupancy/toll (HOT) lane are based on the congestion level in the lane and change as frequently as every 6 minutes.

* Final version: January 2006.

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This regulates demand and, in theory, would better reflect marginal cost pricing. On the SR-91 express lanes, also in southern California, prices are fixed in advance but vary many times throughout the day based on typical general purpose lane congestion (Yan et al., 2002). Several bridges in New York and two in Florida vary the toll based on time of day, with peak-period tolls greater than off-peak (Burris and Pentyala, 2002).

Although these projects are not pure marginal cost pricing, they do represent a step in that direction. Tolls are greater during periods of peak demand when the marginal cost of travel is higher, primarily due to increased travel time. More importantly, the projects provide significant insight into how travelers react to sub-optimal, but practical, congestion pricing scenarios. Due to the increased interest in this form of pricing, it is important to begin an examination of the methods that will be required to incorporate congestion (or value) pricing options into transportation demand models and calibrate these models based on the data from the few operational variable toll projects.

Traditional transportation planning models often use empirical evidence to develop and predict future peak-hour demand. For example, deriving demand using (a) historical trends or (b) using the Institute of Transportation Engineers' trip generation book (Institute of Transportation Engineers, 2003) (see trip generation in Figure 1a). These models, and most others currently used in practice, have no ability to alter the time of travel for a portion of the trip-making population due to tolls that vary by time of day or congestion levels. The models route travelers to the least-cost (generally the shortest time) path from their origin to their destination during the peak period being examined. When examining potential solutions to congested conditions, peak-hour demand is held constant while supply improvements (for example new lanes) are examined.

Recently, several regions around the United States have developed activity and tour-based models for their transportation planning purposes (Donnelly, 2004). These models have the potential to incorporate time of day shifts in travel patterns. They differ significantly from the traditional four-step model shown in Figure 1a. Activity based models develop travel demand profiles by aggregating trip tours over the population of the region. Time of day is incorporated by modeling entire trip tours, not just single, unidirectional trips. For example, if a trip to work is shifted to an early morning departure time due to a variable toll, the model would also shift the return trip to an earlier time of day. Therefore, in theory, a variable toll could be added to such a model resulting in changes to the time of tours. However, this has
not yet been accomplished. One reason is that survey data is required to build the model and to determine the likelihood (percentage) of travelers shifting their trip tour times due to the variable toll or any other change in the cost of travel. This research examines some of the important aspects in developing such a model.

This research examined the operational framework for easily incorporating congestion pricing into a traditional transportation planning model. For example, adding this option to a traditional four-step model (see Figure 1b). In this simplified model (Figure 1b), the travel patterns and disutility
of travel are initially developed for all travelers in the entire morning period (for example, 5:00 a.m. to 11:00 a.m.) The model then examines all drivers to see if traveling at a different time would increase their utility of travel. If yes, the departure time is altered for those travelers and the model run again, repeatedly, until the distribution of departure time, routes, and modes approaches an optimal scenario for those travelers. Another option would be updating activity-based models to include variable tolls. This research develops and tests a basic version of the former model for reasonableness compared to traffic patterns on existing toll facilities with variable tolls. The research also discusses the next steps towards the formal development of a model that incorporates time of day tolling and the data requirements for that model.

**Model development**

Due to limited budgets and increased construction costs, transportation planners are looking for less expensive solutions to congestion problems. However, the possibility of altering the peak-period demand through variable tolls (congestion pricing) is not often examined. There are numerous reasons for this, two of the most important being negative political reaction to tolls and a lack of knowledge of how these tolls might impact congestion. Incorporating congestion pricing options into existing transportation planning models is an important first step in overcoming the latter hurdle, and possibly the former as well.

As previously mentioned, traditional travel demand models have examined peak-period traffic as a given input and distributed this traffic by route and mode. Travel route is determined primarily by the shortest path, with respect to travel time, between the traveler’s origin and destination.

With the addition of a flat toll, modelers then have to incorporate this toll on the tolled routes and predict the resulting travel demand. One method is to estimate the toll price-demand elasticity and the resulting drop in traffic for a given toll increase. Experience from existing toll roads indicate this elasticity is typically around -0.15 to -0.35 depending on the options available to travelers (Burris, 2003). Due to a lack of examples, there is no empirical evidence in the United States of the resulting traffic change when a toll is added to a previously untolled road or bridge.

Another method estimates the travel time equivalent of the toll. For example, assume the toll was $1 and the average traveler’s value of travel time savings was $10 per hour. In this method, the toll road would be modeled as a non-toll route that requires an additional 6 minutes of travel time over
the actual travel time. However, inaccuracies arise due to the non-uniform distribution of traveler's value of travel time savings.

A third method to estimate the resulting traffic demand after a toll increase (or even after a toll is added to a previously untolled roadway) is to add this toll to the total user cost of travel on the route with the toll road/bridge. This method is more complex due to the drivers' differing reactions to a toll. One of the primary factors influencing travelers' willingness to pay is their value of travel time savings. With adequate data, it is possible to estimate the distribution of the value of travel time savings among the likely users of the facility. Then, given (a) their distribution of values of travel time savings, (b) the toll level, (c) the travel time on the toll road, and (d) the travel time on the untolled alternatives, it is possible to derive the number of vehicles using each toll or untolled facility at an equilibrium point.

The following simplified example will be used to illustrate this. In the case of managed lanes the freeway is divided into untolled lanes and tolled lanes (SR-91 in California, and, in the near future, I-15 in California and I-10 in Houston). In these cases, potential users of the tolled (managed) lanes are basically from the same driving population as the untolled lanes. Assume these travelers have a uniformly distributed value of travel time savings from $6/hour ($\text{VoT}_{\text{Min}}$) to $15/hour ($\text{VoT}_{\text{Max}}$). (Note that recent studies show that a lognormal distribution is more likely to occur in practice, but the uniform distribution shown here simplifies the exposition without sacrificing any necessary accuracy.) Also assume that the travel time on the three general purpose lanes and two managed lanes (per direction) varies with traffic volumes as shown in the modified, updated Bureau of Public Roads (BPR) formula (Nakamura and Kockelman, 2002) shown in Equation [1]. (Note again that many speed-flow relationships are available, but a simple one based on the BPR formula allows for additional clarity in this example.)

$$t = t_o \cdot \left[1 + 0.02 \left(\frac{V}{Q}\right)^{10}\right]$$  \[1\]

where

- $t = \text{travel time (minutes)}$
- $t_o = \text{uncongested travel time (minutes)}$
- $V = \text{volume of vehicles per hour (vph)}$
- $Q = \text{capacity at level of service C (vph)}$

Assume a toll of $\text{St}$. Then the equilibrium point is where just enough travelers switch from the general purpose lanes to the managed lanes such that the travel time savings for those paying to use the managed lanes is equal
Figure 2. Travel Times for Given Volumes.

Figure 3. Amount of Travel Time Saved in the General Purpose Lanes Managed Lanes.
to or greater than that group's value of travel time savings. Continuing the example, assume a total demand of 12,000 vph \( (V_{tot}) \), a toll (\( \tau \)) of $2, each lane having a capacity (\( Q \)) of 1700 vph, and an uncongested travel time (\( t_o \)) of 20 minutes. This results in travel times as shown in Figure 2.

When the 12,000 vehicles are distributed on the five lanes, the resulting travel time savings for the general purpose lanes (relative to travel times on the managed lanes) are shown in Figure 3. Of particular importance is the range of volumes where the managed lanes offer a small travel time savings (see inset in Figure 3) as this is where equilibrium will occur. If the managed lanes offer larger travel time savings, then more drivers will choose those lanes and reduce the time savings. If the managed lanes offer a smaller time savings, then fewer travelers will choose those lanes, increasing congestion on the general purpose lanes and increasing the travel time savings on the managed lanes.

To find this equilibrium point, one must simultaneously solve Equations [2] through [5]:

\[
\frac{\tau}{t_{GP} - t_{MG}} - \frac{V_{0}T_{Min}}{V_{0}T_{Max} - V_{0}T_{Min}} \times V_{Tot} = V_{ML} \quad [2]
\]

\[
V_{ML} = \sqrt[10]{\frac{Q_{ML} \cdot (t_{ML} - t_o)}{0.02 \cdot t_o}} \quad [3]
\]

\[
V_{GP} = \sqrt[10]{\frac{Q_{GP} \cdot (t_{GP} - t_o)}{0.02 \cdot t_o}} \quad [4]
\]

\[
V_{GP} + V_{ML} = V_{Tot} \quad [5]
\]

where

- \( t_{GP} \) = time required to travel the general purpose lanes (hour)
- \( t_{ML} \) = time required to travel the managed lanes (hour)
- \( V_{GP} \) = volume of vehicles on the general purpose lanes (vph)
- \( V_{ML} \) = volume of vehicles on the managed lanes (vph)
- \( Q_{GP} \) = capacity of the general purpose lanes (5100 vph)
- \( Q_{ML} \) = capacity of the managed lanes (3400 vph)


In this example, 7451 vehicles choose the general purpose lanes, and 4549 choose the managed lanes. This offers managed lane travelers a time savings of 10.36 minutes.
for a $2 toll, an equivalent of $11.58 per hour. With values of travel congestion ranging uniformly from $6 per hour to $15 per hour, approximately 38,454 vehicles) of travelers would pay the toll, thus achieving equilibrium driver can unilaterally alter their route and decrease their cost of travel.

Although complex, these issues can be addressed by some of the advanced travel demand models used on, for example, the Katy Freeway lanes project. The next step in this evolution will be models for planners to estimate demand by time of day due to a toll rate with time of day. A variable toll would encourage a percentage of the vehicles to move to less congested time periods (rather than simply between general purpose or managed lanes during the peak period). However, this time shift is beyond the ability of most planning models; they do not offer convenient methods to shift vehicles to alternative day or the ability to estimate the percentage that would shift base toll rates. The next section provides an outline of what would be to add such a feature.

Principal factors influencing a driver's time of travel

The first step towards incorporating the impact of a variable toll transportation planning model is to understand the factors (or variables) that impact a traveler’s reaction to variable pricing. To simplify this, the following paragraphs focus on the morning peak traffic period (but not identical) efforts would be required for evening peak periods (DePalma and Lindsey, 2002).

A great deal of theoretical research has been performed in examining driver departure times (Small, 1982; Jauffred and Berns, Chu, 1995) and how the presence of a variable/congestion toll may influence those departure times (Bernstein, 1993; Arnott et al., 1990; Arnott et al., 1988; Lam, T., 2000). In its most basic form, the three primary factors that most influence the traveler’s choice of departure time from home are:

1. penalty for early departure ($\beta$),
2. penalty for late arrival ($\gamma$ and $\Theta$), and
3. disutility of travel time ($\alpha$).

For an individual traveler ($i$), with a preferred arrival time at work, Figure 4 depicts this traveler’s disutility of travel throughout the period based on his or her time of departure, $t_d$. 
Based on Figure 4, this traveler's optimal departure time from home is \( t_d^* \), where the total disutility of the trip is minimized. For a heterogeneous group of travelers, these departure times would vary between travelers, and even vary on a day-to-day basis for the same traveler. However, in aggregate, the values of \( t_{work} \) are similar enough, and the value of \( \beta \) is small enough, to cause individuals to choose similar departure times \( (t_d) \) resulting in congestion on the roadway and the peaking of the time cost of travel.

With congestion/variable pricing, the cost of travel is raised during the peak (or decreased in the off-peak) such that the disutility of traveling during the peak exceeds the disutility of off-peak travel for a portion of travelers. Those travelers alter their time of departure, reducing peak-period congestion and increasing the overall throughput of the roadway. However, this shifting of travel times must be an option in transportation planning models prior to measuring the effectiveness of such a toll in comparison to other congestion relieving options.

**Basic model of departure time selection**

Using the variables outlined above, a simplified model was developed to examine the optimal departure times for individuals. In this model, assume a group of travelers have similar origins and destinations such that they use the same freeway. These travelers all start work at the same time, \( t_{work} \). Also assume we have obtained the values of \( \beta, \gamma, \Theta, \) and \( \alpha \) for these travelers and they were found to vary as follows:

- The penalty for early departure is equal to \( \beta \) at 5:00 a.m. and uniformly decreases to 0 at 7:30 a.m. or anytime thereafter. The slope is therefore \(-\$\beta/150 \) minutes. \( \beta \) is uniformly distributed from \$1\) to \$10 over the traveling population.
The penalty for late arrival is equal to $\gamma$ per minute after 8:00 a.m.; distributed from $0.01$ per minute to $0.50$ per minute. An additional $\Theta$ occurs if the traveler arrives after 8:00 a.m. $\Theta$ is uniformly distributed from $0$ to $10$.

- The disutility of travel time is equal to $\alpha$ per minute. $\alpha$ is uniform from $0.10$ per minute to $0.25$ per minute ($6$ per hour to $15$ per hour)

Assuming a free flow travel time of 20 minutes and a simple model (Vickrey, 1969) to determine travel time under congestion conditions, the following trip cost (focusing on only those three variables greatly impact departure time) is estimated:

$$C(t) = \mu \cdot \beta \cdot \left( \frac{7.30a.m. - t_d}{150} \right) + \varphi \left[ \Theta + \gamma \left( \frac{Q(t_d)}{S} + t_d + 20 - \right) \right] + \alpha \left[ \frac{Q(t_d)}{S} + 20 \right]$$

where

- $C(t)$ = cost of travel at time $t$
- $\mu$ = a dummy variable equal to 1 for early departure and 0 for on-time departure
- $f$ = a dummy variable equal to 1 for late arrival and 0 for on-time departure
- $Q(t_d)$ = queue of traffic that occurs for vehicles leaving at time of departure
- $S$ = maximum hourly flow of vehicles through the bottleneck causing congestion

In theory, all travelers attempt to minimize this cost function with respect to their individual characteristics. To examine how this might work in a planning model, a simplified version of this stochastic model was developed in Visual BASIC (Microsoft, 1998). If the user inputs many of the traveling population’s characteristics, however, in this simple model, the time when the penalty function value equals the value of the entire trip is the same for the entire trip.

The following data were used to test the model. First, assume for travel (2000 vph) is less than the maximum allowable flow at the bottleneck location (2100 vph). All of the travelers have $t_{work}$ of 8; therefore wish to leave after 7:30 a.m. but arrive at work before 8:00 a.m. Ignoring congestion, all travelers would therefore begin their trip at 7:30 a.m. and 7:40 a.m. This is the starting point for the model—the departure time for each vehicle evenly between the time with the penalty function value equal to the value of the entire trip being minimized.
Welcome - Enter Variable Values and Ranges for Analysis of Time of Travel

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Figure 5. Data Input Screen for Toll Model.

would begin, assuming free flow conditions. However, congestion ensues as the 10-minute flow of 2000 vehicles greatly exceeds the 10-minute capacity of the bottleneck of 350 vehicles. Next, the model determines the congested time and cost of travel for each vehicle and begins to redistribute the travelers’ times of departure \( t_{ij} \) according to their randomly generated values of time, penalties for late arrivals, and penalties for early departures.

In this example, many drivers (those with high values of time and high penalties for late arrival) will choose to leave before 7:30 a.m. to avoid congestion and avoid arriving late to work. A few travelers (those with high values of time and a high penalty for early departure) will leave later to avoid congestion. Using the values outlined above, the modeling software was run 20 times for those 2000 hypothetical travelers. Multiple runs were necessary to account for the randomness specifically designed into the model.

Searching for the minimum cost of travel \( C \) for each traveler was an iterative process as travel time both influenced, and was influenced by, the cost of travel. The model converged on a reasonable (but not necessarily optimal) solution in only a few iterations. (Also, to ensure results did not include any part of the transient period, only the last five iterations from each model run were analyzed.) In developing the model, the optimal solution was not selected as that would not be experienced in actual traffic scenarios. Instead, the travelers search for a preferred time of departure that is close to their
current departure time, but 100 percent of the travelers di
t heir travel patterns to the optimal times for the entire group
cates the decrease in total cost (for all travelers) by iteration
Figure 6 it is clear that little improvement in total costs was
four iterations.

Figure 7 indicates the average distribution of $t_d$ over the f
ions for all 20 model runs. Despite the fact that the 2000 t
of time and penalties for late arrival or early departures all
ably, the results were relatively consistent over the 20 model
absolute relative difference for the percentage of vehicles d
any particular minute was 33 percent. The average total co
early departure penalty, and late arrival penalty) for the 200
$9250 (or $4.63 per traveler).

The model results appear reasonable and are intuitive. (g
basic scenarios were modeled, and those results were a
providing further confidence that the model was accurately
traveler behavior as input.) In this model, the majority of t
their time of departure to an earlier time of day to arrive a
the penalty for late arrival. In the 20 model runs, 90.3 perc
left prior to 7:30 a.m., 7.3 percent of travelers left after 7:30 a
before 8:00 a.m., and 2.4 percent left after 7:30 a.m. and at

![Graph showing total cost vs iteration number.](image-url)
Figure 7. Distribution of Departure Times ($t_d$) for Travelers (Note 7:30 am would be 150 minutes after midnight on the graph).

Although the demand (2000 vehicles) was less than the hourly capacity (2100 vehicles) of the roadway, a limited amount of congestion occurred on the roadway, as shown in Figure 8.

Next, a variable (by time of day) toll similar to the one in Lee County, Florida, (Burris and Pendyala, 2002) was added to the trip. In this model, the discount toll was $0.25 and was charged just before (6:30 a.m. to 6:59 a.m.) and just after (9:00 a.m. to 11:00 a.m.) the peak period. At all other times the toll was $0.50. Lee County tolls were similar to these and were designed to encourage travelers to leave the peak period (7:00 a.m. to 9:00 a.m.) without sacrificing off-peak revenues more than necessary. For example, offering a toll discount at 3:00 a.m. would do little to alter peak-period congestion and would simply decrease toll revenues. The toll is shown in Figure 9, along with travel times both prior to and after the toll was applied.

The model was run another 20 times with the new average total cost of travel (for all travelers) of $9868, which includes average toll revenues of $834. Total travel time for all 2000 travelers decreased from an average of 21.2 minutes prior to the toll to 20.9 minutes with the toll. Model results indicated that some travelers (those with lower $\alpha$ and $\beta$, but higher $\gamma$) choose to travel in the off-peak, reducing congestion and the associated delays (see Figure 10). Although the total cost of travel increased by $618, it was by
$236 less than that of the toll revenue. If toll revenues were transferred to travelers, the overall welfare of travelers increases as congestion decreases by having those most able (least impacted) to leave the highway and travel in the off-peak. Although this represents only a 2.6 percent increase in welfare, it was based on a scenario where the capacity of the bridge (2100 vph) actually exceeded demand (2000 vph). In the case of congestion, the welfare savings can be considerably higher.

Similar to the results from actual bridges in Lee County, Florida, with variable tolls, a small percentage of travelers altered their time of departure to take advantage of the off-peak toll discounts (Burris and Penrod 2008). In the model presented here, the percentage of vehicles departing before 7:00 a.m. increased from 26.1 percent without the toll to 28.9 percent with the toll, an increase of 10.7 percent. The Cape Coral Bridge experiment showed an increase of 10.1 percent during the early morning toll discount period.

Similarly, the variable tolls on the Port Authority of New York and New Jersey crossings induced a 11.7 percent shift (from 11.1 percent to 12.2 percent) in traffic to the early morning off-peak period. The fact that these percentages are similar to the one in the model is far from proof of correct, but does provide some reassurance it is on the right track.
County and New York experiences were very different. In Lee County, travelers switching to the off-peak reduced their toll only a small amount and generally, experienced no travel time savings. Conversely, New York travelers reduced their toll by a smaller percentage but by a larger dollar amount, and also saved travel time. Thus indicating the importance of including all travel costs when developing this model for any region with its own specific traffic and toll characteristics.

The heterogeneity of travelers makes this both an effective method of congestion reduction and difficult to model. The values of $\alpha$, $\beta$, $\gamma$, and $\epsilon$ all vary considerably, and there is little empirical evidence of their values even the driver socio-economic and commute characteristics that influence their values. Some theoretical work is available that estimates these values based on survey results (e.g., Small, 1982; Lam, 2000). However, more research is needed on stated preference and revealed preference surveys performed on facilities with variable/congestion tolls in place. This information is a key building block toward adding time of day variable tolls to planning models.
**Next steps**

The model developed here was for illustrative purposes and to begin the steps necessary for development of models for wide-scale next step includes detailed data collection, particularly from travelers basing their travel decision, at least in part, on a facility with toll. This data should focus on three primary items:

1. collecting the factors which most influence traveler's choice of travel time in the case of the morning commute trip,
2. examining the respondents to identify segments of the population reactions/particular reaction patterns to the variable toll, and
3. developing the mean and distribution of values for the variables identified for each population segment identified in (2).

Having been involved in a pair of operational value pricing project author can attest to the difficulties that will be encountered with data. In all likelihood, a large stated preference and revealed preference survey would yield the best results. This form of survey with researchers to validate/weight stated preference results with revenue observations. The stated preference aspect is an important
survey as drivers are faced with a limited choice set in the real world (even with variable tolls) resulting in too little variation in the independent variables to develop a model sensitive to small changes in toll cost, departure time, or arrival time.

Therefore, a logical next step is to collect this information and develop models that can become subroutines incorporated into the newer activity based models. As more areas develop and adopt these activity based models the variable toll subroutines will allow planners to readily investigate the potential impact of variable tolls along with other congestion mitigation options.

Conclusion

This research examined the complexities surrounding adding a toll that varies by time of day (variable/congestion pricing) to transportation planning models. Since travel time both influences, and is influenced by, drivers’ times of departure, any model that allows temporal shifting of travelers will require an iterative calculation process. One such model was developed here to investigate the feasibility of adding this component to travel demand models.

Based on the literature, three variables were chosen to determine each driver’s preferred time of departure. These included the value of travel time savings, a penalty for early departure, and a penalty for late arrival. Each driver was assigned a random value for each of these characteristics, and using the model, their departure time and cost of travel were determined. However, the distribution of these values among the driving population, and the adequacy of using only these three variables, requires further research.

The model successfully distributed vehicles across the rush hour in a logical pattern. When a variable toll was added to the total cost of travel, some drivers altered their times of travel to receive the lower toll rate. The next steps are to collect the data required to incorporate a model such as this one into a transportation planning model that allows temporal (plus route and mode) shifting for travelers. In that manner transportation planners can evaluate the potential of variable pricing to alleviate congestion problems and rank it against other potential solutions.

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Abbonamento annuo (2007) per l'Italia privati Euro 295,00; Enti (con edizione Online) Euro 495,00.

Prezzo del fascicolo singolo: Euro 170.

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