Evaluation of Road Pricing Policy with Semi-Dynamic Combined Stochastic User Equilibrium Model

Ryo KANAMORI *1 Tomio MIWA *2 Takayuki MORIKAWA *3
Graduate School of Environmental Studies, Nagoya University *1
(C1-3 (651), Furo-cho, Chikusa-ku, Nagoya City, Japan, 464-8603, +81-52-789-3730, kanamori@trans.civil.nagoya-u.ac.jp)
Department of Civil Engineering, Nagoya University *2
(C1-3 (651), Furo-cho, Chikusa-ku, Nagoya City, Japan, 464-8603, +81-52-789-3565, miwa@civil.nagoya-u.ac.jp)
Graduate School of Environmental Studies, Nagoya University *3
(C1-3 (651), Furo-cho, Chikusa-ku, Nagoya City, Japan, 464-8603, +81-52-789-3564, morikawa@nagoya-u.jp)

This study analyzes the effect of road pricing policy using a model that 1) incorporates trip generation (i.e. activity choice), destination choice, mode choice, and route choice; 2) considers variations in hourly traffic conditions, including queue evolution; and 3) approximately reproduces the trip chain along the time axis. An evaluation of road pricing policy in the Nagoya Metropolitan Area shows that the policy can improve the environment by reducing the number of car trips that are taken. At the same time, it greatly reduces the number of visitors to the city center by promoting a destination change and only a small shift from cars to railways.

**Keywords:** Road Pricing, Transport Demand Forecasting, Combined Stochastic User Equilibrium Model

1. Introduction

Over-dependence on the automobile has led to chronic traffic congestion and air pollution in Nagoya City. Improvements of road and railway networks as well as transportation or travel demand management (TDM) have implemented to achieve more appropriate automobile usage. Recently, considerable attention has focused on one TDM policy, road pricing, which has proved very successful in Singapore and London. Because travelers must pay to use the roads, they may change their route, mode, destination, departure time, and even choose not to travel. Such changes in traveler behavior also affect the conditions of the road network. Evaluating road pricing policy requires a model that can calculate the equilibrium state of traffic supply and demand in the transportation network.

Many studies have used the equilibrium model to evaluate road pricing policy in urban areas. May and Milne [1] evaluate various road pricing systems in Cambridge (in the UK), including cordon-based, distance-based, time-based, and congestion-based charging. Santos [2] simulates cordon pricing in eight English towns. The model used in these studies, however, does not explicitly express traveler behavior because it uses an elastic assignment model. Maruyama and Sumalee [3] use an elastic demand model, even though they compare cordon-based and area-based charging using an innovative trip-chain equilibrium model. On the other hand, Maruyama et al. [4] analyze the effects of road pricing in the Tokyo Metropolitan Area with a model that considers a traveler’s mode choice, route choice, and both car and railway network congestion. Furthermore, de Palma et al. [5] take into account the departure time, mode choice, and route choice in their dynamic equilibrium simulator. Gentile et al. [6] utilize multi-class assignment in a multimodal network that includes trip generation, modal split, and route assignment. Although some of these studies expressed traveler behavior, none included destination choice. Yet, as noted above, road pricing policy yield a change in destination as well as route choice. In this study, we improve the evaluation model by introducing destination choice.

The objective of this study is to develop a combined user equilibrium model that includes activity choice and the time dimension—that is, a semi-dynamic combined stochastic user equilibrium model—and to evaluate road pricing policies in the transport network of a real metropolitan area. The model developed in this study has the following characteristics. First, the model considers traveler’s activity choices (by integrating trip generation, destination choice, mode choice and route choice). Thus it is able to measure induced traffic by a change in traffic conditions. Traveler choice behavior is assumed to be expressed as a nested logit structure, which is based on random utility maximization theory. The developed model also allows for hourly variations in travel time resulting from both changes in traffic congestion and the
frequency of public transit services. Finally, the trip chain is approximated by computing in sequence the equilibrium state in each time period. For this purpose, we deal with activity related to staying (not traveling), intra-zonal O-D trips and walking trips. The model is formulated using a mathematical optimization approach, resulting in a unique solution that is the equilibrium state. These characteristics of the model make it possible to evaluate road pricing policies (in this study, cordon-based road pricing) in detail.

2. Model Formulation

2.1. Semi-dynamic Traffic Assignment Model with Queue Evolution

The semi-dynamic traffic assignment model with queue evolution, as formulated by Akamatsu et al. [7], is based on certain assumptions. First, the time period $T$ (in this study, $T$ is set to one hour) is longer than any travel time between an origin-destination (O-D) pair, and the traffic state in each time period is assumed to be static. Traffic state transitions occur only at transitions between time periods. Second, each link consists of an un-congested segment and a congested segment. The former is the segment representing vehicular flow, and the passage time is expressed by the usual link performance function. The latter is an outflow terminal node with a vertical queue. Consequently, a state transition can be expressed by equation (1) and the travel time on a link by equation (2).

\[
\begin{align*}
X_a^T &= X_a^{T-1} + x_a^T - \mu_a \quad \text{if} \quad X_a^T > 0 \\
X_a^{T-1} + x_a^T &\leq \mu_a \quad \text{if} \quad X_a^T = 0
\end{align*}
\]  

(1)

where $x_a^T$ is the inflow rate on link $a$ in time period $T$, $X_a^T$ is the queue on link $a$ in $T$, $X_a^{T-1}$ is the queue formed in the previous time period (and treated as a constant in $T$), and $\mu_a$ is the maximum discharge rate calculated from the potential capacity of link $a$.

\[
t_a^T = t_a(x_a^T) + \max(0, X_a^{T-1} + x_a^T - \mu_a, 0)/\mu_a
\]  

(2)

where $t_a^T$ is the travel time on link $a$ in time period $T$ including time lost waiting in any queue, and $t_a(\cdot)$ is the link performance function (i.e. the BPR function).

The time-dependent traffic state in time period $T$ is formulated as an equivalent minimization problem. Each time-dependent traffic state is achieved independently of other time periods on condition that the flow remnants are given as constants. In addition, $x_a^{T^*}$ in the equilibrium state is calculated by a normal solution algorithm (e.g. the Frank-Wolf method) substituting $t_a(\cdot)$ as calculated with the usual link performance function with $t_a^T$ as given by equation (2). $X_a^{T^*}$, calculated using equation (1), is treated as the flow remnants on link $a$ in the next time period if it is non-zero.

2.2. Traveler Behavior

We assume that the behavior of travelers in each time period is expressed as the nested logit structure shown in Figure 1. This structure considers activity choice, destination choice, mode choice, and route choice behavior.

![Figure 1. Structure of the traveler choice process in each time period](image)

2.3. Formulation of Semi-dynamic Combined Stochastic User Equilibrium Model

The travel time on each link in the road network is expressed by equation (2). In addition, prices (such as expressway tolls) are converted into time terms according to the value of time for each activity. Link travel time varies according to the inflow rate on the link and the path flow, which is the result of traveler behavior. At the same time, the generalized travel time in the behavioral model varies according to the link travel time. Thus, we need to seek an equilibrium state between demand and supply in each time period $T$. This equilibrium state can be obtained by solving the following equivalent convex minimization problem—the Semi-dynamic Combined Stochastic User Equilibrium Model which is one of a multi-class user equilibrium model. Since each time-dependent traffic state is achieved independently of the other time periods on condition that the flow remnants and the number of people present at each location in each zone are given constants, the expression is simplified by omitting from the following equation the subscript representing a specific time period ($T$).
\[
\text{min. } Z = \sum_{a} \int_{0}^{t_a} \rho_a(\omega) d\omega + \sum_{a} \left[ \max\left( X_{a}^{-1} \cdot x_a, 0 \right) \right]^{2} \frac{1}{2 \mu_a} \\
+ \sum_{a} \frac{1}{\theta_m} f_{i, m, k}^{l, rs} \ln \left( f_{i, m, k}^{l, rs} \right) + \sum_{m} f_{i, m, k}^{l, rs} \mu_{m}^{l, rs} \\
+ \sum_{i, r, s, m} \frac{1}{\theta_s} q_{m, s, i, r}^{l, rs} \ln \left( q_{m, s, i, r}^{l, rs} \right) + \sum_{s} q_{m, s, i, r}^{l, rs} v_{s, l}^{l, rs} \\
+ \sum_{i, r, s} \frac{1}{\beta_r} O_{r, i}^{l, rs} \ln \left( O_{r, i}^{l, rs} / N_{r, l} \right) + \sum_{l} O_{r, i}^{l, rs} \ln \left( O_{r, i}^{l, rs} / N_{r, l} \right) \\
+ \sum_{i, r, l} O_{r, i}^{l, rs} \ln \left( O_{r, i}^{l, rs} / N_{r, l} \right) \\
\text{subject to } x_a = \sum_{i, r, k, a} f_{i, m, k}^{l, rs} \delta_{a, k}^{l, rs}, \forall a \tag{3b} \\
\sum_{k} f_{i, m, k}^{l, rs} = q_{m, s, i, r}^{l, rs}, \forall i, r, s \tag{3d} \\
\sum_{m} q_{m, s, i, r}^{l, rs} = O_{r, i}^{l, rs}, \forall i, r \tag{3f} \\
\sum_{l} O_{r, i}^{l, rs} = O_r, \forall r \tag{4d} \\
O_{r, i}^{l, rs} + O_{r, i}^{l, rs} = N_{r, l}, \forall r, l \tag{3h} \\
f_{i, m, k}^{l, rs} \geq 0, \quad q_{m, s, i, r}^{l, rs} \geq 0, \quad O_{r, i}^{l, rs} \geq 0, \quad O_r \geq 0, \quad O_{r, i}^{l, rs} \geq 0, \quad O_{r, i}^{l, rs} \geq 0 \tag{3i}
\]

where \( f_{i, m, k}^{l, rs} \) is the path flow by each mode for each activity, \( q_{m, s, i, r}^{l, rs} \) is the O-D trips by each mode for each activity, \( O_r \) is the number of trips generated by each activity, \( O_{r, i}^{l, rs} \) is the number of trips generated by each activity in each location, \( O_r \) is the number of people staying at the same location, \( N_{r, l} \) is the number of people who stayed in the same zone or made a trip in the previous time period, \( T_{a, k}^{l, rs} \) is 1 if the link is on \( k \) th path between an O-D pair by each mode and 0 otherwise, \( p_a \) is the price or charge on the link, \( t_a \) is the value of time for each activity, \( C_{m, k}^{l, rs} \) is the generalized travel time on the \( k \) th path between an O-D pair by each mode for each activity, \( V_m^{l, rs}, V_r^{l, rs} \) and \( V_r^{l, rs} \) are systematic components of each choice, and \( \theta_1^{l, rs}, \theta_2^{l, rs}, \theta_3^{l, rs} \) are scale parameters.

It can be proved easily that this problem has a unique solution under these conditions (3b-i). The Kuhn-Tucker conditions for the problem lead to the aforementioned nested logit model with stochastic user equilibrium conditions.

\[
f_{i, m, k}^{l, rs} = \frac{\exp(-\theta_1^{l, rs} C_{m, k}^{l, rs})}{\sum_k \exp(-\theta_1^{l, rs} C_{m, k}^{l, rs})} \tag{4a} \\
q_{m, s, i, r}^{l, rs} = \frac{\exp(-\theta_2^{l, rs} (V_m^{l, rs} + S_m^{l, rs}))}{\sum_m \exp(-\theta_2^{l, rs} (V_m^{l, rs} + S_m^{l, rs}))} \tag{4b} \\
S_m^{l, rs} = -\frac{1}{\theta_3^{l, rs}} \ln \sum_k \exp(-\theta_1^{l, rs} C_{m, k}^{l, rs}) \tag{4c} \\
O_r = \exp(-\theta_2^{l, rs} (V_r^{l, rs} + S_r^{l, rs})) \tag{4e} \\
O_{r, i}^{l, rs} = \exp(-\theta_2^{l, rs} (V_r^{l, rs} + S_r^{l, rs})) \tag{4f} \\
S_r^{l, rs} = -\frac{1}{\theta_3^{l, rs}} \ln \sum_r \exp(-\theta_2^{l, rs} (V_r^{l, rs} + S_r^{l, rs})) \tag{4g}
\]

where \( S_m^{l, rs}, S_r^{l, rs} \) and \( S_r^{l, rs} \) are inclusive values.

The partial linearization algorithm [8] can be used to efficiently solve this problem. Even though the problem includes a path-flow entropy term, the model can be applied to large networks using entropy decomposition as shown by Akamatsu [9]. Figure 2 shows a more practical calculation procedure for achieving equilibrium traffic states in each time period. As this demonstrates, the equilibrium state in each time period is determined from traveler activity and from traffic conditions in the previous time period, and from the zone characteristics. Note that in the first time period only those dwelling within each zone are treated as being present in the zone. In this way, the model can represents the trip chain along the time axis through the equilibrium states in each time period.
3. Application to Nagoya Metropolitan Area

This paper briefly describes the developed model's application to the Nagoya Metropolitan Area. Please refer to our previous studies for details [10, 11].

3.1. Input Data and Given Parameters

In order to apply the developed model to an actual situation, in this case the Nagoya Metropolitan Area, the model parameters must be estimated. Travelers behavior in this area was obtained from the 4th Nagoya Metropolitan Area Person Trip (PT) Survey conducted in 2001. The parameters are estimated based on this PT survey data by means of the maximum likelihood method.

Traffic conditions reported by the PT survey are assumed to correspond to the stochastic traffic equilibrium state. The average hourly travel time on every road link is calculated from a ‘Link Cost Table’ developed using probe-vehicle data gathered in the Nagoya Metropolitan Area [12]. The average time per hour of travel by railway and bus is calculated from the timetables. Estimates of model parameters, as well as the analysis, are based on the PT minimum size zone, in which Nagoya City is divided into 258 zones with an average area of 1.25 km². Data representing zone characteristics (such as area and population) are obtained using Geographical Information Systems. We also consider intra-zonal O-D trips, the level-of-service of which is set to zero for car and bicycle travel and walking. Vehicle occupancy is assumed to be 1.0. The positive scale parameter for a car in route choice is set to 0.5 (1/minute). For drivers, the value of time is set to 83.4 JPY per minute for the activities of commuting to work and to school and business travel. The corresponding value for private trips and returning home is 43.9 JPY per minute. These values are also estimated based on the 4th Nagoya Metropolitan Area PT survey data preparatory to estimating the model parameters. The inclusive value of the driver’s route choice is calculated from the link weight value of Dial’s algorithm [13].

3.2. Estimation of Model Parameters

3.2.1. Route Choice and Mode Choice. First, we estimate the parameters of route choice and mode choice for each activity. The estimation results are shown in Table 1. The route choice model considers only car and railway travel because of the work involved in developing alternative route data. The parameters of the route choice model are common to all activities. Level of service, socio-economic characteristics and parking charges are adopted as explanatory variables. Every parameter has the expected sign and is statistically significant. The calculated value of in-vehicle time for railway travel is 22.1 JPY per minute, and out-of-vehicle time is valued at 36.5 JPY per minute. Intuitively, these values seem appropriate. The calculated value of in-vehicle time for bus travel is 10.2 JPY per minute and out-of-vehicle time is valued at 6.3 JPY per minute. Intuitively, these values seem low. This may be due to the flat fare system used by urban transport services in Nagoya City. For the mode choice for private and business trips, the model considers influence of the pre-trip mode, which is the same as in the previous trip. Similarly, a dummy, which is given a value of 1 when the selected mode is the same as that for leaving home, is introduced in the mode choice for returning home.

3.2.2. Destination Choice. Next, we estimate the parameters of the destination choice model for each activity. In this case, the destination choice for returning home is excluded because the destination is fixed (the home zone). The parameters are estimated from a set of
twenty randomly selected alternative choices, since the true number of alternatives is huge (about 300 zones).

Some zone characteristics are adopted as explanatory variables. A ‘Same zone dummy’ is introduced for intra-zonal O-D trips. The estimation results are shown in Table 2. Every parameter has the expected signs and is statistically significant. Since the scale parameters are smaller than those in the mode choice model, the assumption of a nested logit structure is satisfied. In the destination choice for commuting to school and for private trips, the estimated distance between the O-D pairs in addition to the inclusive value, is estimated negative because the chosen destinations tend to be nearby.

### 3.2.3. Activity Choice

Finally, we estimate the parameters of the activity choice model in each location (Home, Workplace/Study place, Other place). The activity choices are appropriately set for each location, occupation and the activity history. For instance, “commuting to work” is set only for a worker who has not arrived at his/her workplace. In addition, since home-to-work and home-to-school trips are daily habitual daily activities, it is assumed that these activity choices are not influenced by accessibility (inclusive value). Thus, the scale parameter for home-to-work and home-to-school trips is set to zero.

Socio-economic characteristics and current activity duration are adopted as explanatory variables. The estimation results are shown in Table 3. Every parameter has the expected signs and is statistically significant. Since the scale parameters are smaller than those in the destination choice model, the assumption of a nested logit structure is satisfied. In these models, it is the case that the temporal utility profiles of activities [14, 15] are expressed by dummy variables according to the specific time period.

<table>
<thead>
<tr>
<th>Table 1. Estimation results of route choice and mode choice</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mode Variable</strong></td>
</tr>
<tr>
<td>Car</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Railway</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 2. Estimation results of destination choice</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Variable</strong></td>
</tr>
<tr>
<td>Scale parameter</td>
</tr>
<tr>
<td>Area (ha)*1</td>
</tr>
<tr>
<td>log Worker per area (person/ha)</td>
</tr>
<tr>
<td>log Employee per area (person/ha)</td>
</tr>
<tr>
<td>log Student per area (person/ha)</td>
</tr>
<tr>
<td>log Shop per area (office/ha)</td>
</tr>
<tr>
<td>log Office per area (office/ha)</td>
</tr>
<tr>
<td>log Factory per area (office/ha)</td>
</tr>
<tr>
<td>log School and Hospital per area (office/ha)</td>
</tr>
<tr>
<td>log extension of road per are (m²/km)</td>
</tr>
<tr>
<td>log O-D distance (km)</td>
</tr>
<tr>
<td>log O-D distance age under 15 (km)*2</td>
</tr>
<tr>
<td>School dummy*3</td>
</tr>
<tr>
<td>Shop dummy*3</td>
</tr>
<tr>
<td>Same zone dummy (in Nagoya city)*4</td>
</tr>
<tr>
<td>Same zone dummy (out of Nagoya city)*4</td>
</tr>
<tr>
<td>Log likelihood at convergence</td>
</tr>
<tr>
<td>Adjusted McFadden’s Rho-squared</td>
</tr>
</tbody>
</table>

*1: This parameter is set 1 if the area is the same as the one in the pre-trip, otherwise is 0.
*2: Average parking charge in destination that is calculated from the PT data
*3: Out of home mode dummy is 1 if the mode is something other than commuting to home, otherwise is 0.
*4: Average parking charge in destination that is calculated from the PT data
3.3. Model Validation

The model set up with the parameters estimated in the previous section was applied to the Nagoya Metropolitan Area. The road network consists of 22,466 links and 7,606 nodes. We use a BPR type link performance function with parameters recently estimated in Japan [16, 17]. Since freight data is not included in the PT survey data, this data is based on the Road Traffic Census O-D Survey of 1999. It is assumed that freight vehicles make trips between fixed O-D pairs and that the value of time is 87.4 JPY per minute, as calculated by the Japan Society of Civil Engineers [16].

In order to validate traffic states, this study sets 3:00 a.m. as the time at which number of residents in each zone is determined. For the convergence condition of the equilibrium calculation, traffic in each level is assumed to change by less than 1% and the equilibrium calculation is done 5-8 times in each time period.

Figure 3. Total numbers of trips generated

Figure 4. Modal share of Nagoya City

Table 3. Estimation results of activity choice

<Home>

<table>
<thead>
<tr>
<th>Activity</th>
<th>Variable</th>
<th>Scale parameter [Private-Business]</th>
<th>Commuting to Work</th>
<th>Commuting to School</th>
<th>Commuting</th>
<th>Private</th>
<th>Business</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.009</td>
<td></td>
<td></td>
</tr>
<tr>
<td>log(Current activity duration+1.0)(hour)</td>
<td>0.314</td>
<td>9.75</td>
<td>7.54</td>
<td>1.80</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time period dummy_8-11_worker</td>
<td>-</td>
<td>-</td>
<td>0.206</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time period dummy_15-19_student</td>
<td>-</td>
<td>-</td>
<td>0.874</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Time period dummy Details are omitted for the space saving.

Number of samples 20,712
Log likelihood at zero -216,568.8
Log likelihood at convergence -29,769.4
Adjusted McFadden’s Rho-squared 0.862

** All estimated values are different from 0 with 5% statistical significant level.

<Work place/Study place>

<table>
<thead>
<tr>
<th>Activity</th>
<th>Variable</th>
<th>Scale parameter</th>
<th>Commuting to Work</th>
<th>Commuting to School</th>
<th>Commuting</th>
<th>Private</th>
<th>Business</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.009</td>
<td></td>
<td></td>
</tr>
<tr>
<td>log(Current activity duration+1.0)(hour)</td>
<td>0.064</td>
<td>-</td>
<td>1.45</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>log Current activity duration [arrival before 16]</td>
<td>0.860</td>
<td>-</td>
<td>0.68</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>log Current activity duration [arrival after 17]</td>
<td>0.862</td>
<td>-</td>
<td>1.08</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Time period dummy_12-14_female-worker | -                  | -               | 1.64              | -                   |           |         |          |
Time period dummy_15-16_female-worker | -                  | -               | 1.32              | -                   |           |         |          |
Time period dummy_15-17_female-worker | 1.78              | -               | 1.78              | -                   |           |         |          |
Time period dummy_12-14_student | -                  | -               | 1.91              | -                   |           |         |          |
Time period dummy_15-16_student | -                  | -               | 2.84              | -                   |           |         |          |
Time period dummy_15-17_student | 1.57              | -               | 1.57              | -                   |           |         |          |

Time period dummy Details are omitted for the space saving.

Number of samples 6,034
Log likelihood at zero -72,026.0
Log likelihood at convergence -15,669.0
Adjusted McFadden’s Rho-squared 0.782

** All estimated values are different from 0 with 5% statistical significant level.

<Other Place>

<table>
<thead>
<tr>
<th>Activity</th>
<th>Variable</th>
<th>Scale parameter</th>
<th>Commuting to Work</th>
<th>Commuting to School</th>
<th>Commuting</th>
<th>Private</th>
<th>Business</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.033</td>
<td></td>
<td></td>
</tr>
<tr>
<td>log(Current activity duration+1.0)(hour)</td>
<td>-0.916</td>
<td>-</td>
<td>-1.28</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>log Current activity duration [arrival by private purpose]</td>
<td>-</td>
<td>-</td>
<td>0.049</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>log Current activity duration [arrival by business purpose]</td>
<td>-</td>
<td>-</td>
<td>-0.989</td>
<td>-1.25</td>
<td>-1.34</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Work dummy</td>
<td>-</td>
<td>-</td>
<td>1.96</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time period dummy_10-12_non-worker</td>
<td>-</td>
<td>-</td>
<td>0.408</td>
<td>-</td>
<td>0.426</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time period dummy_13-16_non-worker</td>
<td>-</td>
<td>-</td>
<td>0.515</td>
<td>-</td>
<td>0.699</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time period dummy_10-12_over 65 age</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.271</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Time period dummy Details are omitted for the space saving.

Number of samples 6,619
Log likelihood at zero -19,074.1
Log likelihood at convergence -11,961.9
Adjusted McFadden’s Rho-squared 0.371

** All estimated values are different from 0 with 5% statistical significant level.
underestimation after 1 p.m. is evident. One reasonable explanation for this tendency to underestimate the number of trips generated is that we assume travelers will not make more than one trip in each time period. As shown in Figure 4, the share of railway is overestimated even though the estimate for the share for cars is fairly good. Furthermore, with a correlation coefficient of 0.84 and a regression coefficient of 0.92, the reproducibility of the car link flow is relatively good.

These results largely validate the developed model for large-scale transportation planning, even though it tends to somewhat underestimate the total number of trips.

4. Evaluation of Road Pricing Policy

The developed model can serve as a primary analysis for evaluating cordon road pricing policy. Cordon road pricing is a system by which road users entering a cordoned area must pay a charge. By introducing a road pricing policy, road users will change their choice of route, mode, destination, departure time, and even the decision of whether to travel or not. The developed model considers activity choice, destination choice, mode choice and route choice. The departure time decision, which is a main effect of London’s road pricing policy [18], is not considered due to model complexity. Such consideration is a task for future studies.

In order to compare the effect of various cordon areas and price levels in Nagoya City, the following cases of charging are introduced, with charging from 7:00 a.m. to midday.

- **Case_0**: No change.
- **Case_1** (700 JPY): Cordon area shown by inner line; Price level is 700 JPY
- **Case_1** (1500 JPY): Cordon area shown by inner line; Price level is 1,500 JPY
- **Case_2** (700 JPY): Cordon area shown by outer line; Price level is 700 JPY
- **Case_2** (1500 JPY): Cordon area shown by outer line; Price level is 1,500 JPY

![Figure 5. Cordon lines in case studies](image)

**Price level is 700 JPY**

- **Case_2** (1500 JPY): Cordon area shown by outer line; Price level is 1,500 JPY

The inner and outer cordon boundary lines are shown in Figure 5. The inner line encloses the city center while the outer line encompasses most of Nagoya City. The price is converted into travel time by the value of time for each activity.

Figure 6 is a comparison of the number of trips attracted to Nagoya City. Every case with pricing shows little change from Case_0 (with no pricing) in the total number of trips, although the number of car trips is lower to some extent in all cases (in Case_1_700: -6%; in Case_1_1500: -10%; in Case_2_700: -7%; and in Case_2_1500: -12%). Figure 7 compares the number of trips to the city center. The total number of trips attracted to the city center is reduced by 7-11% in the Case_1 series, where the cordon is the inner line. In particular,
Case_1_1500 leads to 55% fewer car trips. It turns out that within the city center where the railway network is sufficiently developed, the shift from car to railway is smaller than we expected, and the number of visitors for private and business is reduced sharply.

According to Table 4, which shows the changes in O-D trips, car trips from the outer city center {{2} and {3}} to the inner area {{1}} are reduced sharply compared to Case_0 (in Case_1_700: -55%; in Case_1_1500: -75%). As a result, the total number of private trips is much smaller than we expected, and the number of visitors for car trips from the outer city center {{2} and {3}} is reduced sharply compared to Case_0 (in Case_1_700: -55%; in Case_1_1500: -75%).

Judging from the small shift from car to railway, the decision to change destinations or not to travel arises within Nagoya City to the city center (in Case_1_700: lower, even though more railway trips are made from the inner area {{1}} are reduced sharply compared to Case_0 (in Case_1_700: -55%; in Case_1_1500: -75%).

While a road pricing policy may benefit the environment, such a policy may be very difficult to implement because, among other reasons, stakeholders would object to the sharply fewer trips to the area controlled by the road pricing policy, as noted above. This commonly reported phenomenon of road pricing policy is also seen in this study. Further research is needed on other pricing systems, such as area-based pricing and distance-based pricing, as well as on the inequity issue.

At the same time, a more elaborate model for evaluating road pricing policy is needed. Although the developed model described incorporates some traveler behaviors as an evaluation tools for case studies, this change is almost the same for each price level regardless of the cordon size. Average speed and time lost in traffic jams are also improved in all cases, although these effects within the city center are much better in the Case_1 series than in the Case_2 series. As a result of these changes, CO2 emissions are greatly reduced after the introduction of a road pricing policy. Changes in the road network flow are shown in Figure 9. We can see that the road traffic flows within the cordon are reduced by about 20% while the flows of links along the cordon and on expressways are increased as traffic is diverted. If the area surrounded by the cordon is small, as in Case_1_700, this reduction covers the whole area.

While a road pricing policy may benefit the environment, such a policy may be very difficult to implement because, among other reasons, stakeholders would object to the sharply fewer trips to the area controlled by the road pricing policy, as noted above. This commonly reported phenomenon of road pricing policy is also seen in this study. Further research is needed on other pricing systems, such as area-based pricing and distance-based pricing, as well as on the inequity issue.

At the same time, a more elaborate model for evaluating road pricing policy is needed. Although the developed model described incorporates some traveler behaviors as an evaluation tools for case studies, this change is almost the same for each price level regardless of the cordon size. Average speed and time lost in traffic jams are also improved in all cases, although these effects within the city center are much better in the Case_1 series than in the Case_2 series. As a result of these changes, CO2 emissions are greatly reduced after the introduction of a road pricing policy. Changes in the road network flow are shown in Figure 9. We can see that the road traffic flows within the cordon are reduced by about 20% while the flows of links along the cordon and on expressways are increased as traffic is diverted. If the area surrounded by the cordon is small, as in Case_1_700, this reduction covers the whole area.

While a road pricing policy may benefit the environment, such a policy may be very difficult to implement because, among other reasons, stakeholders would object to the sharply fewer trips to the area controlled by the road pricing policy, as noted above. This commonly reported phenomenon of road pricing policy is also seen in this study. Further research is needed on other pricing systems, such as area-based pricing and distance-based pricing, as well as on the inequity issue.

At the same time, a more elaborate model for evaluating road pricing policy is needed. Although the developed model described incorporates some traveler behaviors as an evaluation tools for case studies, this change is almost the same for each price level regardless of the cordon size. Average speed and time lost in traffic jams are also improved in all cases, although these effects within the city center are much better in the Case_1 series than in the Case_2 series. As a result of these changes, CO2 emissions are greatly reduced after the introduction of a road pricing policy. Changes in the road network flow are shown in Figure 9. We can see that the road traffic flows within the cordon are reduced by about 20% while the flows of links along the cordon and on expressways are increased as traffic is diverted. If the area surrounded by the cordon is small, as in Case_1_700, this reduction covers the whole area.

While a road pricing policy may benefit the environment, such a policy may be very difficult to implement because, among other reasons, stakeholders would object to the sharply fewer trips to the area controlled by the road pricing policy, as noted above. This commonly reported phenomenon of road pricing policy is also seen in this study. Further research is needed on other pricing systems, such as area-based pricing and distance-based pricing, as well as on the inequity issue.

At the same time, a more elaborate model for evaluating road pricing policy is needed. Although the developed model described incorporates some traveler behaviors as an evaluation tools for case studies, this change is almost the same for each price level regardless of the cordon size. Average speed and time lost in traffic jams are also improved in all cases, although these effects within the city center are much better in the Case_1 series than in the Case_2 series. As a result of these changes, CO2 emissions are greatly reduced after the introduction of a road pricing policy. Changes in the road network flow are shown in Figure 9. We can see that the road traffic flows within the cordon are reduced by about 20% while the flows of links along the cordon and on expressways are increased as traffic is diverted. If the area surrounded by the cordon is small, as in Case_1_700, this reduction covers the whole area.
Figure 8. Changes in private trips attracted to each zone

Table 5. Effect on road traffic and environmental situation

<table>
<thead>
<tr>
<th></th>
<th>Vehicle-Kilometers</th>
<th>Average Speed</th>
<th>Loss Time in Traffic Jam</th>
<th>CO₂ emissions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Nagoya city</td>
<td>Nagoya city</td>
<td>City Center</td>
<td>Nagoya city</td>
</tr>
<tr>
<td>Case 1 700</td>
<td>-7.6%</td>
<td>+0.39</td>
<td>+0.86</td>
<td>-88.1</td>
</tr>
<tr>
<td>Case 1 1500</td>
<td>-13.1%</td>
<td>+0.67</td>
<td>+1.49</td>
<td>-54.2</td>
</tr>
<tr>
<td>Case 2 700</td>
<td>-7.3%</td>
<td>+0.26</td>
<td>+0.01</td>
<td>-88.7</td>
</tr>
<tr>
<td>Case 2 1500</td>
<td>-12.8%</td>
<td>+0.53</td>
<td>+0.24</td>
<td>-100.7</td>
</tr>
</tbody>
</table>

Note: change ratios from Case 0 in vehicle-kilometers and CO₂ emissions; changes from Case 0 in average speed (unit: km/h) and time lost to traffic jams (unit: h).
model ignores the choice of departure time. This results in an overestimation of the number of visitors to the area controlled by the road pricing policy. Furthermore, the model may underestimate the number of visitors because it calculates a different work-place/study-place in each case. Evaluations of the short-term effect of a road pricing policy are more realistic if the workplace is fixed beforehand. However, this may be difficult to do because several million people are involved.

5. Conclusion

In this study, we developed a Semi-Dynamic Combined Stochastic User Equilibrium Model that overcomes or reduces the drawbacks of conventional traffic flow models. The developed model features the following characteristics: 1) It includes traveler activity choices and integrates trip generation (activity choice), destination choice, mode choice and route choice, allowing induced traffic to be measured; 2) It assumes that traveler’s choice behavior is expressed as a nested logit structure based on random utility maximization theory; 3) It considers hourly variations in travel times resulting from changes in traffic congestion and the frequency of public transit services, and includes explicit calculation of the time lost in traffic jams; 4) Trip chains along the time axis are approximately modeled; 5) It uses a mathematical optimization approach.

In order to validate the developed model, it was applied to the large-scale transportation network of the Nagoya Metropolitan Area. The results demonstrate the potential of the developed model to effectively compare various policies and evaluate in detail the effects of comprehensive urban transport planning. However, the modeling needs further refinement.

An evaluation of cordon-based road pricing policy confirmed that the environment is effectively improved as a result of the considerably reduced number of car trips that are taken. The improvement is even greater if the area surrounded by the cordoned area is small and the price is higher. On the other hand, the policy also decreases the number of visitors to the area since there is little transfer of trips from car to railway and users tend to change their destination. It may be difficult for stakeholders to agree to the introduction of such a pricing policy because of this reduction in the number of visitors. Therefore, further studies are needed on alternative road pricing systems, such as area-based pricing and distance-based pricing, as well as on the inequity issue. Detailed analysis of comprehensive urban transport plans also is needed.

References

R. Kanamori Dr. of Eng. (Nagoya University, 2007). Research Fellow, Graduate School of Environmental Studies, Nagoya University. Member of JSCE, CPIJ, WCTRS and EASTS.

T. Miwa Dr. of Eng. (Nagoya University, 2005). Assistant Professor, Department of Civil Engineering, Nagoya University. Member of JSCE, CPIJ and JSTE.

T. Morikawa Ph.D. (MIT, 1989). Professor, Graduate School of Environmental Studies, Nagoya University. Member of JSCE, CPIJ, JSTE, JIMS, WCTRS and EASTS.

* Received date: December 12, 2007
□Received in revised form: May 7, 2008
□Accepted date: June 30, 2008
□Editor: Toshio Yoshii