Introducing Congestion Pricing as a Key to Reducing Road Congestion

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Abstract: Congestion Pricing is believed to have an adverse effect on demand for roads wherein motorists react to different congestion pricing policies by decreasing their demand for road use. On the other hand, it is also of equal importance to consider the Pareto improvement by determining the congestion price that could reduce the traffic congestion and enhance the social welfare of motorists. Our group developed a well-designed guide that presents the process of arriving at the congestion price that could aid future road planning. To ensure the validity and accuracy of our guide, we tested it on a small-scale sample at the Nichols-Merville Exit area (Southbound) along South Luzon Expressway (SLEX) and West Service Road (WSR). We conclude that the currently imposed toll charge in SLEX does not effectively solve the congestion problem and is not welfare enhancing for the road users.

Key words: congestion pricing, second-best, value of travel time

1. INTRODUCTION

How can we get the Pareto-efficient congestion charge that facilitates mobility and maximizes social welfare?

Traffic congestion greatly contributes to poor traveling conditions experienced by both public and private commuters. Researchers have attempted to solve this problem by altering the supply of roads such as changing infrastructure and promoting other more efficient modes of transportation. Some studies have considered changing the demand for roads through imposing a tax or charge on a certain road network during peak and off-peak hours. Such proposition is called congestion pricing which is effective in various places such as London, Stockholm and Singapore.

London, in particular, implemented in 2003 one of the most extensive road pricing projects that resulted to increased traffic speeds by 37%, dropped congestion by 40% during charging hours, and reduced round-trip travel time by 13%, only eight months after implementation (Peng, 2003).

In the Philippines, road pricing schemes are seen in the form of toll ways in major expressways that charge according to destination and vehicle type. Aside from this, the Metro Manila Development Authority (MMDA) has implemented various congestion-control programs aiming to combat the traffic congestion experienced in many roads such as the Unified Vehicular

Volume Reduction Program (UVVRP) or more popularly known as the "color-coding" system implemented since 1996. However, congestion pricing has never been tested in any of the roads in the country (Pangilinan, 2007).

Finding the right or optimal congestion price is a major problem in congestion pricing. Verhoef and Koh (2008), with the use of capacity and toll instruments, considered 'long-run cost functions' for congested networks in solving second-best network problems. On the other hand, Win, Kubota and Sakamoto (2007) tested the effectiveness of various congestion pricing schemes – time based scheme, distance based scheme, and area wide scheme – using the tiss-NET simulation-based prediction method.

The abovementioned studies delve into a common problem present in several countries: road congestion. In fact, statistics show that the demand for vehicle usage has continued to grow in the Philippines that have been causing roads to become increasingly congested. Statistics from Philippine National Statistical Coordination Board for years 2002-2007 show that there is a constant increase in registered vehicles which would result to inevitable traffic congestion in the roads regularly travelled given the supply of roads is relatively fixed over time. This traffic congestion experienced at certain times of the day considered as "rush" or "peak" hours invokes a need for a better policy to reduce congestion.

1.1 Objectives

Our study aims to:

1. Provide a detailed guide on how the Pareto-efficient congestion price can be obtained.
2. Analyze the travel behavior and characteristics of motorists who regularly pass through the chosen roads.
3. Investigate the validity of the study by performing a small-scale sample of the said procedure in the Nichols-Merville exit area along SLEX and West Service Road (WSR).

1.2 Scope and Limitations

The study exhibits several limitations that must be taken note of. These include the following:

1. The application of the procedure due to time and budget constraints is on a smaller scale and is less extensive than what would normally be required to implement policies.
2. The study was tested on an area (SLEX) that already has an existing toll charge. This can potentially cause bias in the data gathered for demand on the tolled route.
3. Road maintenance costs are not considered in computing for the Pareto-efficient congestion charge.
4. The accuracy of the data is not absolute due to the confidential variable income.

2. REVIEW OF RELATED LITERATURE

2.1 Congestion Pricing as an Example of Taxes Modify Motorists' Behavior

Since traffic congestion is a prevalent problem in different countries, governments employ different policies to try to alleviate it. The policies that have been launched includes price congestion schemes aimed to reduce car volume in congested areas considering the additional concerns of environmental sustainability and value of time among the urban population. As we try to support the notion that congestion pricing as a tax is an effective way to modify motorists' behavior, we cite a number of governments' use of surveys in channeling it into implementation.

The Thai government surveyed the public's response to road congestion pricing using 200 random samples across 6 districts of capital Bangkok to explain the effect of implementing a price congestion strategy. When asked whether or not they would support a price congestion policy in the country, 70% of the respondents overwhelmingly reacted negatively, 22% positively, and 8% neutrally (Kunchornrat et al., 2007) that strongly signifies the great potential in reducing traffic congestion with charging a particular amount for road usage.

Singapore has incorporated price congestion policies in its set of policies in seeking to attain an overall decrease in traffic congestion. Over the years it has implemented different schemes each addressing the country's current predicament. More so, it monitored and controlled these policies by tailoring the present policy according to the current needs of the country in order to maintain or further increase social welfare. Its policies pose as a real-life example of a successful price congestion policy, attaining favorable results using a refined version of their original Electronic Road Price (ERP) System first launched in 1998 (Lew and Leong, 2009). This refined price policy included a move towards making the price charges more visible to motorists by showing live time traffic conditions, giving them more control in choosing their routes and thus controlling their expenses.

The continuous changes in the policies over the years point out the flexibility of price congestion policies in addressing different transportation efficiency problems in an area. In Singapore's case, it revised its price congestion policies according to materializing issues in its transport system. It shifted its priorities from loosening congestion in their business district to controlling the number of vehicles in the country using the Vehicle Quota System that eventually led to the launch of ERP System that lowered price congestion charges. So far, the ERP system has been improved twice to expand its visibility that aims to give the motorists more control and break down the cost they incurred through a deconstructed expense (Lew and Leong, 2009). Indeed, transportation plays a big role in facilitating economic growth even in more developed countries. Researchers have committed themselves to searching for an area-specific price congestion system and catering to increase individual and social welfare.

2.2 Determining Pareto-Efficient Congestion Charge

2.2.1 Types of costs considered

Travel time costs and schedule-related costs contribute to congestion costs incurred by road users (Liu & McDonald, 1999). Basically, road users incur travel time costs from passing through certain congested routes during either peak or off-peak periods. The travel time costs fluctuate in response to the traffic volume. Moreover, this cost classification takes a more general scope as compared to the schedule-related cost. The schedule-related cost relates with the changes in the motorist's usual travel schedule. When alterations on motorists' desired time of departure and arrival at his or her destination occur, corresponding congestion costs are incurred according to the schedule-related costs' bracket. These two cost classifications, help in finding out how much it would take for motorists to consider taking another route or adjust to different departure times. Considering motorists' rational attitude, we can say that they would choose to avoid congested areas and peak hours if these would lead them to acquire additional costs and disadvantages. Therefore, when congestion costs increase, motorists would rationally alter their travel patterns accordingly either by changing routes or changing departure times, which would consequently lead to a reduction in traffic congestion in areas where very high congestion costs hinder road use.

2.2.2 Important role of demand elasticity

Other than congestion costs, the demand for road use is another fundamental element in congestion pricing which involves determining the Pareto-efficient price charge. We can solve for the Pareto-efficient set of prices that would equate the marginal cost and the marginal benefit on all links by knowing the origin–destination demand for traveling across a network along with the value of user time savings (Han and Yang, 2009). Considering motorists' rational behavior, we can say that they would always opt to take the route that would give them the highest utility, wherein in this case, is the one with the lowest least travel time. It follows that if road owners or policymakers wish to maximize the social welfare, they would logically choose to reduce travel time through reducing traffic congestion which can be achieved by the help of an effective congestion pricing scheme in accordance with the assumption of having no demand functions.

However, we should make assumptions with regard to the elasticity of these demand functions in order to utilize such demand functions. Using elastic and inelastic demand functions would allow our study's results to greatly vary. Various researches have looked into this topic using different methods of analysis. First is the view utilizing inelastic demand functions where they mainly concern link flows with respect to tolls only. This view constructs algorithms to find out the optimal congestion tolls in the second-best problem (Yan and Lam, 1996). However, considering that motorists act rationally by aiming to minimize their costs and to maximize their welfare, assuming inelastic demand functions becomes a rather unrealistic claim. This means that road users would not alter their demand despite the increasing congestion cost.

The second view that utilizes the elastic demand functions is more realistic since it affirms how the motorists would react if we were to impose a congestion price. In fact, a greater number of researchers which include Hearn, Yildirim and Verhoef support this second view because it focuses more on the subsets of the road links in finding out the optimal congestion charge while assuming that congestion is link-specific. Moreover it assumes that the costs, which represent the generalized user costs, and congestion, which goes in accordance with the rationale behind congestion pricing, relates directly (Verhoef, 2002).

3. FRAMEWORK

3.1 Demand and Supply Characteristics

In road pricing, the demand for road use greatly influences the charge making it an important element to consider. It represents how much motorists want to use a road. So here, aggregate demand for one period or period demand is a function of trip prices during peak and off-peak periods that represent the total traffic volume spanning the entire origin-destination route in one period. However, we followed Liu and McDonald (1999) in assuming that income effect is negligible. Thus we have,

$$\begin{aligned} v_p &= f_p(P_p, P_o) \\ v_o &= f_o(P_p, P_o) \end{aligned} \tag{1}$$

where v_p: traffic volumes for peak period (veh/h)
v_o: traffic volumes for off-peak period (veh/h)
P_p: trip price for peak period
P_o: trip prices for off-peak period

For Eq. (1) demand functions, we assumed the following assumptions regarding dependency: (1) negative own-price effect and (2) positive cross-price effect. The own-price effect suggests that motorists reduce their road usage in response to congestion pricing imposition while the cross-price effect introduces the dependency of period demands on the price of the other period. We can use the latter in the study of the peak shifting problem such as the movement of the peak period trips to the off-peak period, by considering the response of the peak period demand to the off-peak trip price, and vice versa. From Eq. (1), the inverse period demand function, i.e. the trip price for one period, can be derived as a function of the traffic volume in both periods such that:

$$P_p = P_p(v_p, v_o),\ and\ P_o = P_o(v_p, v_o) \tag{2}$$

Given the Eq. (2) inverse demand functions, the gross benefit for the system (B) can be expressed as a line integral

$$B = \int_{(0,0)}^{(v_p, v_o)} P_p(v_p, v_o)dv_p + P_o(v_p, v_o)dv_o \tag{3}$$

However, there are two major problems associated with Eq. (3): (1) the line integral is not unique, and (2) the line integral is not differentiable. The integrability condition below solves both problems (see Pressman, 1970 for a more detailed discussion):

$$\frac{\partial P_p}{\partial v_o} = \frac{\partial P_o}{\partial v_p} \tag{4}$$

On the other hand, road supply is harder to alter since it requires large investments and significant government intervention before additional roads can be created. It is primarily represented by the road capacity. By definition, road capacity is the maximum traffic flow possible on a given roadway at a certain span of time utilizing all available lanes. Often, it is measured in vehicles per hour but in this study, we used vehicles per hour per lane (veh/h/ln) to be in accordance with the formulations to be used later.

3.2 Price Elasticity of Demand

Knowing the demand elasticity makes us more aware of the effect on demand of a change in a particular factor. Since we are proposing a price congestion scheme, we need to determine the price elasticity of demand among motorists in our chosen congested area. Price elasticity of demand shows the sensitivity of demand to changes in prices and is measured by the rate of response of quantity demanded for a price change. Knowledge of motorists' price demand elasticity enables the determination of the Pareto-efficient congestion charge which reflects the best price charged to motorists for using the tolled route.

If the resulting price elasticity turns out to be low or inelastic, meaning a price change would induce a minimal change in demand, then motorists would still opt to take the tolled route despite the congestion price charged. Alternatively, when the price elasticity is high or elastic, a price change would induce a relatively large change in demand, encouraging motorists to take available alternative routes where congestion cost is less than that of the tolled route. Thus, determining the elasticity level – the magnitude of the effect on demand for road use – paves the way for heightened effectiveness of congestion pricing in reducing traffic on the congestion area through the price elasticity of demand.

3.3 Cost Characteristics

Congestion tends to increase road user costs since it induces schedule delay costs in addition to vehicle usage costs. This suggests that the cost function of an individual road user is composed of travel time costs and schedule-related costs. Theoretically, higher income travelers would have higher value of schedule delay as compared to lower income travelers.

To incorporate both the travel time and schedule-related costs of congestion, we have an average cost function based from Liu and McDonald (1999) denoted by

$$c_{ir}(v_{ir}),\ i = p, o;\ r = t,\ f \tag{5}$$

where $c_{ir}(v_{ir})$ = average cost of using route r at time period i
v_{ir} = traffic volume on route r on period i
i = time period (p = peak period; o = off-peak period)
r = route choice (t = tolled route; f = free route)

It should also be assumed that the average cost is an increasing function of the traffic volume. Thus, we can derive the marginal cost and total cost functions that are both essential to the study of congestion pricing. The marginal cost is:

$$MC_{ir} = \frac{d[v_{ir}c_{ir}(v_{ir})]}{dv_{ir}} = c_{ir}(v_{ir}) + v_{ir}c'_{ir}(v_{ir});\ i = p, o;\ r = t,\ f. \tag{6}$$

And the total cost incurred by all travelers for each route and for each period in the system is defined as:

$$C = [v_{pt}c_{pt}(v_{pt}) + v_{pf}c_{pf}(v_{pf})] + [v_{ot}c_{ot}(v_{ot}) + v_{of}c_{of}(v_{of})] \tag{7}$$

3.4 Second-best Model

Patterning our study to the model by Liu and McDonald (1999), we have a constrained optimization program for the second-best problem that aims to maximize net benefits or welfare (W) given by:

$$\max W = B - C$$

$$= \int_{(0,0)}^{(v_p,v_o)} P_p(v_p, v_o)dv_p + P_o(v_p, v_o)dv_o - [v_{pt}c_{pt}(v_{pt})] - [v_{pf}c_{pf}\,f(v_{pf})] \tag{8}$$

subject to constraints:

$$P_p(v_p, v_o) = c_{pf}(v_{pf}) = c_{pt}(v_{pt}) + \tau_{pt}, \tag{9}$$

$$P_o(v_p, v_o) = c_{of}(v_{of}) = c_{ot}(v_{ot}) + \tau_{ot}, \tag{10}$$

$$v_p = v_{pt} + v_{pf};\ v_o = v_{ot} + v_{of}, \tag{11}$$

$$v_{pt} \geq 0,\ v_{pf} \geq 0,\ v_{ot} \geq 0,\ v_{of} \geq 0,\ v_p \geq 0,\ v_o \geq 0 \tag{12}$$

where τ_{pt} = congestion toll on tolled route during peak period
τ_{ot} = congestion toll on tolled route during off-peak period

Eq. (9) gives us the constraint on pricing the toll route during the peak period particularly that the equilibrium price of a trip on either route during the peak period should be equal to the average cost on the free route and also to the average cost plus the congestion toll during the peak period. Eq. (10) gives a similar constraint as Eq. (9) but this one applies to the off-peak period. Eq. (11) states that the total traffic volume in the peak (off-peak) period equals the sum of the traffic volume on each route in the peak (off-peak) period. Lastly, Eq. (12) shows the non-negativity conditions for traffic volumes.

By solving the model for allocating optimal traffic volume (v_{pt}, v_{pf}, v_{ot}, v_{of}, v_p, v_o) particularly Eq. (11), the second-best congestion tolls (τ_{pt} , τ_{ot}) for both periods can be determined by:

$$\tau_{pt} = P_p(v_p, v_o) - c_{pt}(v_{pt}), \text{ and } \tau_{ot} = P_o(v_p, v_o) - c_{ot}(v_{ot}) \tag{13}$$

To solve the model given above, we will utilize a Lagrangian given by

$$\begin{aligned} L(v_{pt}, v_{pf}, v_{ot}, v_{of}, v_p, v_o) &= B(v_p, v_o) - C(v_{pt}, v_{pf}, v_{ot}, v_{of}) - \lambda_p[P_p(v_p, v_o) - c_{pt}(v_{pt})] \\ &\quad - \lambda_o[P_o(v_p, v_o) - c_{of}(v_{of})] - \mu_p[v_p - v_{pt} - v_{pf}] - \mu_o[v_o - v_{ot} - v_{of}] \end{aligned} \tag{14}$$

After getting the first-order conditions of the Lagrangian, we apply P_{ij} to it which is the partial derivative of $P_i(v_p, v_o)$ with respect to v_j:

$$P_{ij} = \frac{\partial P_i}{\partial v_j}, i, j = p, o. \tag{15}$$

We can then obtain the simplified equations for (v_{pt}, v_{pf}, v_{ot}, v_{of}, v_p, v_o) by eliminating v_p, v_o, λ_p, λ_o, μ_p, μ_o:

$$P_p(v_p, v_o) = MC_{pt} + \lambda_p P_{pp} + \lambda_o P_{op} \tag{16}$$

$$P_p(v_p, v_o) = c_{pf}(v_{pf}) \tag{17}$$

$$P_o(v_p, v_o) = MC_{ot} + \lambda_p P_{po} + \lambda_o P_{oo} \tag{18}$$

$$P_o(v_p, v_o) = c_{of}(v_{of}) \tag{19}$$

$$v_{pt} \geq 0, v_{pf} \geq 0, v_{ot} \geq 0, v_{of} \geq 0 \tag{20}$$

These equations are the optimality conditions of the model for each route and period. As you can see in Eq. (16), the equilibrium price of the toll route in the peak period is the marginal cost of passing through it plus certain price adjustments that have to be made.

From this model, we can arrive with the optimal price for both periods. Since the demand for road use during peak hours is relatively high, we anticipate the congestion price during that period to be higher compared to the off-peak period.

3.5 Solution for the Second-best Congestion Pricing Model

Since we have covered the theoretical aspect of our study, we are now ready to solve it. The solution would require us to simplify the equations presented above and solve them numerically as it would be very difficult to solve it analytically. In going about our solution, we will generally input real values gathered and follow these necessary steps: (1) specify cost function, (2) specify demand function, (3) estimate parameters, and (4) solve equations via Newton's method.

3.5.1 Specify the cost function using the Bureau of Public Roads (BPR) function

The average cost $c_{ir}(v_{ir})$ comprises of the travel time costs and schedule-related costs:

$$c_{ir}(v_{ir}) = \alpha T_{ir} + \beta S_i, i = p, o; r = t, f. \tag{21}$$

where T_{ir}: road user's travel time (h)
S_i: road user's schedule delay time (h)
α: value of travel time (pesos/h)
β: value of schedule delay (pesos/h)

We get the travel time T_{ir} by employing the BPR function (Koppelman and Bhat, 2006).

$$T_{ir} = T_r^0 \left[1 + 0.15 \left(\frac{v_{ir}}{K_r} \right)^4 \right], i = p, o; r = t, f. \tag{22}$$

where T_r^0: uncongested or free flow travel time (h of route r)
K_r: certain level of capacity (veh/h of route r)

Since capacity level (K_r) is below the maximum flow in route r, the traffic volume (v_{ir}) may exceed capacity level (K_r). Such is possible because the capacity level identified is based on an assumption that all cars are moving in the same ideal traffic flow speed but in reality, the car speeds vary significantly and so will the traffic volume in the area. For the schedule-related time, S_p = 0 because there are no schedule delays when the road users are able to pass by the peak period as it is assumed that they prefer to pass by the area during that period. However, S_o is assumed to be a constant value which we can obtain from the survey results.

By substituting Eq. (24) BPR function in Eq. (23) average cost function, we may rewrite the cost function $c_{ir}(v_{ir})$ as:

$$c_{ir}(v_{ir}) = \gamma_{ir} + \delta_r \left(\frac{v_{ir}}{K_r} \right)^4, \ i = 1,2; r = t, f. \tag{23}$$

where

$$\gamma_{ir} = \alpha T_r^0, if \ i = p$$
$$= \alpha T_r^0 + \beta \overline{S}, \text{if } i = o \tag{24}$$

and

$$\delta_r = 0.15 T_r^0, r = t, f. \tag{25}$$

The derivative of the average cost function $c'_{ir}(c_{ir})$ and the marginal cost MC_{ir} from Eq. (23) to (25) can be computed by Eq. (6)

$$c'_{ir}(v_{ir}) = 4 \left(\frac{\delta_r}{K_r} \right) \left(\frac{v_{ir}}{K_r} \right)^3, \ i = p,o; \ r = t, f. \tag{26}$$

$$MC_{ir} = \gamma_{ir} + 5\delta_r \left(\frac{v_{ir}}{K_r} \right)^4, \ i = p,o; \ r = t, f. \tag{27}$$

We need to assign values to the parameters (T_t^0, T_f^0, K_t, K_f) for us to arrive with our solution. The travel time functions for both tolled and free route using the BPR function in Eq. (22).

3.5.2 Specify demand functions

The demand functions in vehicles per hour (veh/h) for both periods are expressed by linear structures:

$$v_p = Q_p - \beta_{pp}P_p + \beta_{po}P_o, \text{ and}$$
$$v_o = Q_o + \beta_{op}P_p - \beta_{oo}P_o. \tag{28}$$

where Q_p = average demand in peak period
Q_o = average demand in off-peak period
β_{pp} = own price elasticity of peak period
β_{po} = cross price elasticity of peak with respect to off-peak period
β_{op} = cross price elasticity of off-peak period with respect to peak period
β_{pp} = own price elasticity of off-peak period

Parameters should satisfy the assumptions:

1. $Q_p>Q_0>0$. The positive demand in the peak period or the off-peak period.
2. $\beta_{pj}>0, i,j=p,o$. Negative own price and positive cross-price effect.
3. $\beta_{pp}\beta_{oo}-\beta_{po}\beta_{op}>0$. Own-price effects prevail over cross-price effects.
4. $\beta_{po}=\beta_{op}$. Eq. (6) Integrability condition for the inverse demand functions

The inverse demand functions from Eq. (28) can be derived as:

$$P_p(v_p, v_o) = A_p - b_{pp}v_p - b_{po}v_o, \text{ and}$$
$$P_o(v_p, v_o) = A_o - b_{op}v_p - b_{oo}v_o. \tag{29}$$

where

$$A_p = \frac{\beta_{oo}Q_p + \beta_{po}Q_o}{d}; A_o = \frac{\beta_{op}Q_p + \beta_{pp}Q_o}{d} \tag{30}$$

if b_{ij}, $i,j= p,o$ is given by

$$b_{pp} = \frac{\beta_{oo}}{d}, b_{po} = \frac{\beta_{po}}{d}, b_{op} = \frac{\beta_{op}}{d}, b_{oo} = \frac{\beta_{pp}}{d}. \tag{31}$$

where $d = \beta_{pp}\beta_{oo} - \beta_{po}\beta_{op} > 0$ based on the third assumption stating that own-price effects prevail over cross-price effects.

In assumptions 1 to 4, b_{ij}, $i,j = p,o$ in Eq. (31) complies with:

$$b_{ij} > 0, i, j = p, o$$
$$b_{po} = b_{op} \tag{32}$$

$b_{po}=b_{op}$ shows that the demand functions in Eq. (30) satisfies the integrability condition shown by Eq. (4).

Base demand parameters Q_p and Q_o will be obtained through manual counting while the elasticities β_{pp}, β_{po}, β_{op}, and β_{oo} will be obtained through the survey questionnaire.

3.5.3 Estimate parameters *a* and *β* using Nested Logit (NLOGIT) model
Since we need to get the value of travel time and schedule-delay time for the road user, we employed a NLOGIT model to take into account the two road choices the user has. In this model, we capture the utility of the road user with respect to the variables we want to test. Thus, we have the following basic model from Green (2002):

$$U_{jt} = \beta_{jt} X_{jt} + \varepsilon_{jt} \tag{33}$$

where U_{jt} = utility of choice j for an individual t

X_{jt} = variable tested regarding its effect on the utility of the individual t given choice j.

β_{jt} = additional utility or disutility (depending on its sign) of the road user with the variable X_{jt}.

ε_{jt} = error term.

From this basic model, we can apply it to our problem to get the cost parameters: (1) value of travel time, a, and (2) value of schedule-delay, β.

For the NLOGIT model for value of travel time (a), we utilized two variables – travel time (*TTime*) and travel cost (*TCost*). *TTime* is the individual travel time of the users for each road chosen while *TCost* is the total cost of an individual for each road chosen. Specifying the model in Eq. (51) to capture the value of travel time, we have a new model:

$$U_{jt} = \theta_{1jt} TTime_{jt} + \theta_{2jt} TCost_{jt} + \varepsilon_{jt},\ j = t,\ f \tag{34}$$

Here the j choices are limited to two roads only, the tolled route t and the free route f. Both θ_{1jt} and θ_{2jt} are expected to have negative signs since any additional travel time or travel cost respectively would result to disutility for the road user.

In this model, we accounted for both the travel time and travel cost of the road user because according to a study by Antoniou, Matsoukis, and Roussi (2007), the coefficients of these two variables are the road user's sensitivity towards changes in them. Thus, their ratio (coefficient of travel cost over coefficient of travel time) would be the trade-off between travel time and travel cost which is the value of travel time.

On the other hand, for the NLOGIT model for value of schedule-delay (β), we used the schedule-delay (*STime)* variable only to arrive with the value of schedule-delay. Thus, our model is

$$U_{jt} = \beta_{jt} STime_{jt} + \varepsilon_{jt},\ j = t,\ f \tag{35}$$

The j choices here are also limited to two only the tolled route t and the free route f. The *STime* coefficient β_{jt} is also expected to be negative and its absolute value would be equal to the value of schedule-delay β.

3.5.4 Solve equations using Newton's method and base parameters
With the specified cost functions in Eqs. (23) to (25) and the demand functions in Eq. (29), we can get the optimal volume allocations by solving for the nonlinear system of Eqs. (16) to (20) for the second-best model. Using the specified equations and the parameters estimated, we can simplify the equations to arrive with only the volumes as the unknown. With this, we can now utilize Newton's method to numerically solve the solutions to the model. We will run the Newton's method through the SAS software using a pre-programmed script file of the Newton's method process. It yields the following output:

1. optimal traffic volume allocations;
2. congestion tolls, equilibrium average cost, and trip prices

4. METHODOLOGY AND RESULTS

In the previous chapter, we have vaguely covered the main procedures to arrive at the Pareto-efficient congestion toll. This chapter, however, is intended to outline all the steps involved aiming to eliminate all ambiguities presented in the previous chapters. It also details out the process of our small-scale sample in the Nichols to Merville Exit area.

4.1 Define the Area of Study

We have chosen to test our study on the Nichols to Merville Exit area with WSR as the free route and SLEX as the tolled route. This proves to be an appropriate area of study since it has a common point of origin and destination clearly recognized by road users.

4.2 Determine Feasibility of the Study

We verified the feasibility of our area by ensuring that there would be a sufficient number of potential respondents for our survey. We identified homeowners of Merville Village who pass through the chosen area on the way home as potential respondents since the village is situated just a few minutes away from the point of destination, Merville Exit. Since most residents of the said village belong to middle to upper middle class income brackets, it follows that most travel using private vehicles. Moreover, Merville Village is well populated with hundreds of households in it, we were certain that we would reach the target number of respondents.

4.3 Send and Collect Surveys

An important step in implementing congestion pricing is getting the values of the variables and parameters that will be used in solving the Pareto-efficient congestion toll. This can be done by collecting primary data through surveying.

Data on the following must be obtained from the survey: (1) Time at which the respondent passes through the area of study, (2) Road preference, (3) Normal driving speed when passing through the chosen road, (4) Maximum willingness to pay, (5) Direct cost of passing through a road (i.e., gasoline expense and toll fee, if applicable), and (6) Individual monthly income.

Our group conducted house to house survey in Merville Village wherein out of roughly 350 individuals surveyed, 167 responded. The data gathering was conducted over two consecutive weekends, with the authorization of the Merville Village Homeowner's Association.

4.4 Perform Field Testing to Determine Free-flow Travel Time

In order to obtain the standard travel time through the roads for each time period, we measured the time it took us to reach Merville exit from Nichols, driving at an average constant speed of 70 kph and 50 kph for SLEX and WSR respectively.

From the field measurement, the free-flow travel time can be determined based on the least frequently-traveled time for each road. Since we have identified the off-peak time from 10 to 11 pm from the survey results, the free flow travel time for SLEX and WSR are 102.50 seconds or 0.02847217 hours and 160 seconds or 0.044445 hours respectively.

4.5 Get Secondary Data to Determine Road Capacity

An essential element of the entire procedure is to determine the road dimensions (i.e., number of lanes and distance) of both routes which would be used in determining their respective road capacities. Our group was able to secure the data for road dimensions of SLEX by visiting the Traffic Safety Management and Security Department of the Philippine National Construction Corportion (PNCC) Skyway Corporation Office. For road dimensions, SLEX has 3 lanes and a total distance of 1.7 km while WSR has only one lane and a total distance of 1.7 km also.

After collecting the road dimensions from the authority, the next step is to determine the vehicular capacity of each road corresponding to its characteristics. The capacity basically measures the maximum number of vehicles per lane a road can accommodate with reasonable safety during a specified time period (Koppelman & Bhat, 2006). To do this, the general guideline provided by the Highway Capacity Manual (HCM) method may be followed.

In determining the road capacity, the initial step is to classify the road based on the two general categories of traffic flow: (1) *basic freeway segements* and (2) *multilane highways*. The first category assumes the roadway segement to have two or more lanes in each direction, having a minimum lane width of 12 ft while the second assumes a lower road capacity.

Looking at the respective dimensions of each road, it is evident that SLEX (tolled route) offers greater capacity than its alternative because it has a wider lane width.

Ckecking for the conditions outlined by the HCM technique that will determine the category of traffic flow to be used, we found our tolled route SLEX to fall under the category *basic freeway segments* and our free route WSR to fall under the *multilane highways.*

Since we have obtained the free flow travel time for each road, we can then derive the free-flow speed that will have the corresponding capacity by simply applying the basic formula for speed (i.e., distance over time). We have already identified the distance of the road as 1.7 km, so dividing it by the free-flow travel time 0.02847217 hours and 0.044445 hours for SLEX and WSR respectively, we got the free-flow speed for each road as shown in Table 1.

Table 1. Summary of Free-flow Speed for WSR and SLEX

Road	Distance (in km)	Free-flow Travel Time (in h)	Free-flow Speed (in km/h)	Free-flow Speed (in mi/h)
SLEX	1.7	0.02847217	59.71	36.41
WSR	1.7	0.044445	38.24	23.32

From the free-flow speed, we were able to obtain the capacity for each road based on the relationship between free-flow speed and capacity as provided by Koppelman and Bhat (2006). The resulting road capacity for each road is 1,500 vehicles/hour/lane (veh/h/ln) for WSR and 2,050 veh/h/ln for SLEX.

4.6 Perform Manual Counting to Determine Peak and Off-peak Demand

It is necessary to perform manual counting or other counting techniques to determine the quanity of vehicles in the area during peak and off-peak periods. Since we need to count the total number of cars passing through the area for a certain time period, there is a need to have a strategic position that enables one to monitor the quantity of cars that passes through the identified point. This would have to be done for an hour during the peak and off-peak time as identified earlier in the survey results. The resulting volume Q_p and Q_o for peak and off-peak periods respectively would be used in deriving the optimal traffic volumes v_{pt}, v_{pf}, v_{ot}, v_{of}.

Our group chose to perform manual counting on a weekday when congestion emerges as a problem. We performed the said procedure during the peak and off-peak periods as identified in the survey results, 7-8 pm for peak period and 11 am-12 pm for off-peak period. Table 2 summarizes the manual counting results which gives us the values for Q_p and Q_o, where Q_p represents the total number of cars in the chosen area during peak time and Q_o represents the same during off-peak time.

Table 2. Manual Counting Results

Road	Number of Vehicles in veh/h (Peak: 7-8 pm)	Number of Vehicles in veh/h (Off-peak: 11 am-12 pm)
WSR	1113	798
SLEX	270	51
Total	1383	849

Thus, Q_p= 1,383 veh/h and Q_o= 849 veh/h.

4.7 Filter out Data

Filtering data involves two stages. The first stage involves the general dataset: all information encoded wherein there lies a one-to-one (respondent-to-observation) correspondence. For an accurate result later on, each observation in this dataset should encompass values for every variable column.

We performed the first-stage filtering by first forming our general dataset in Microsoft Excel. With observations numbered, each one had to have information given in all information regarding (1) the frequency of passing the Southbound Nichols to Merville Exit area in a workweek, (2) the time he usually passes through the area, (3) his flexibility of passing through the area at a time other than normal, (4) the road he often chooses (SLEX or WSR), (5) speed at the chosen road, (6) when SLEX: negative or positive stance to an increase in the toll price during period he normally passes and when WSR: willingness to pay to pass through SLEX during a time opposite to the period he usually passes, (7) weekly gasoline expense, (8) number of hours driven in a week, and (9) monthly income.

During the second stage of filtering, criterion will vary for every parameter. Since each has special provisions and its values will be computed separately through the two different computer programs NLOGIT and Microsoft Excel, the information from the general dataset will be broken further into special datasets formulated according to the information each needed parameter requires, and the information feed format required by the program.

4.8 Estimate the Parameters

Solving the average cost function in Eq. (21) requires the estimation of the value of travel time (α) and value of schedule delay (β). The estimation would make use of an NLOGIT model with the use of LimDep software. NLOGIT estimates the said parameters by identifying the choice made by each observation given the number of alternative choices available to him.

The first parameter, α, would depend on the choice that would be made by motorists between the two alternative roads available to them. The computation of this parameter will be the quotient of the NLOGIT output of Eq. (34) for the coefficients of *travel time (TTime)* and *travel cost (TCost)*. The *TTime* variable would be the estimated time it takes for each observation to reach the destination point from the point of origin. It requires the length of the road and each observation's speed, computed as:

$$\frac{\text{Road Length}}{\text{Speed}} \times 3600 \tag{36}$$

The result of our NLOGIT regression for the value of travel time resulted to a coefficient of -0.0066 for *TTime* and -0.0498 for *TCost.* Both are statistically significant at 95% confidence level. Dividing these two gives us a value of 0.1325 (in pesos per second) or 7.9518 (in pesos per minute) which is our value of travel time (a).

The signs of the coefficients for both travel time and travel cost are in accordance with our a-priori expectation. They are negative because increasing travel time and cost would cause a certain level of disutility among the motorists. As can be seen, the degree of disutility for incurring additional travel cost is greater than the degree of disutility for incurring additional travel time, which entails that the observations generally value the explict monetary costs of road usage than the implicit time costs. Both variables are significant implying that these

The next variable, *TCost*, refers to the direct costs of road users for passing through their chosen road, specifically the gasoline expense that they spend for passing through the area and the toll fee that they pay in case their road choice is imposing a charge for road use. It requires the observation's travel time and gasoline cost per second, computed as:

$$\text{Travel Time x Gasoline Cost (per sec)} \tag{37}$$

When these values of coefficients are produced through the estimation of Eq. (34), their quotients are able to capture the sensitivity of the travelers' utility toward changes in the travel time and travel cost. Their ratio can therefore be used to capture the trade-off between the travel time and the travel cost.

The second and third parameters β and $\overline{S}$ are the value of schedule delay and schedule delay, respectively. With a prerequisite of an observation's willingness to adjust his travel time other than usual, a crucial variable involved in the process is the determination of shifting time, the amount of time required to shift his time period. That is, if an individual observation's time of passing is a peak period, the adjustment time will be the number of hours until it becomes off-peak. For an observation passing the area during an off-peak period, adjustment time will be the number of hours until it becomes a peak time. This aside, the value of schedule delay associated with the income forgone for having to adjust their travel time from peak to off-peak or from off-peak to peak also requires an individual's monthly income in seconds expressed by the following equation:

$$\beta = \text{amount of shifting time (in seconds) x income (peso per second)} \tag{38}$$

where this value may also be provided when Eq. (35) is run in the NLOGIT program.

The result of our NLOGIT regression for the value of schedule delay shows a coefficient of -0.008 pesos per minute for *STime* and is highly statistically significant at 95% or even 99% confidence level. This is equivalent to 0.481 pesos per second.

The negative sign of the coefficient implies that additional schedule delay would likewise cause disutility to individuals because there is opportunity cost in the form of income foregone.

The third parameter, value of schedule delay ($\overline{S}$), is an average of all observations' shifting time. By getting the average schedule delay, $\overline{S}$ turns out to be 6808 seconds.

Lastly, the set of elasticities to be determined are:
β_{11}: peak road demand elasticity with respect to the change in price during the peak period
β_{21}: off-peak road demand elasticity with respect to the change in price of the peak period
β_{22}: off-peak demand elasticity with respect to the change in price of the off-peak period

The computations of these elasticities adhere to the basic principle of elasticity, expressed by:

$$\begin{aligned}
\beta_{11} &= \frac{\Delta \text{ peak period road demand}}{\Delta \text{ peak period road price}} \\
\beta_{21} &= \frac{\Delta \text{ off-peak period road demand}}{\Delta \text{ peak period road price}} \\
\beta_{22} &= \frac{\Delta \text{ off-peak period road demand}}{\Delta \text{ off-peak period road price}}
\end{aligned} \tag{39}$$

The output values for each of these elasticities deal with different respondents: for β_{11}, included elasticities are observations that normally use the tolled route during a peak time and are asked for their positive or negative stand towards a higher-price road usage during that time; for β_{21}, included elasticities are observations that normally use the free route during an off-peak time and are willing to transfer to a peak time when the peak price decreases to their individual preferred peak price; for β_{22}, included elasticities are observations that normally use the tolled route during an off-peak time and are asked for their positive or negative stand towards a higher-price road usage during that time.

Using averaging, the β_{11} value turns out as -0.0825, the β_{21} value as 0.0602, and β_{22} as -0.0777 where these values satisfy all assumptions established in the previous sections.

4.9 Solve Non-linear Equations Using Newton's Method

In our study, we opted to utilize the SAS program in solving for the nonlinear equations. This was done in accordance with what was used by Liu and Mcdonald (1999) in their study. We initially inputted all the estimated parameters required in the model and we ran the Newton's Method in SAS. The process was completed after fifteen iterations.

The first output given by the SAS program are the optimal volume allocations then the average cost, trip prices, and elasticities shown in Table 4. These values obtained will be used in solving for the Pareto-efficient congestion toll in the next step.

Table 3. Summary of SAS Output Results for Average Cost and Trip Prices

Variables	Output
c_{pt}	13.6458
c_{ot}	75.9033
P_p	21.2764
P_o	81.1329

where: $\boldsymbol{c_{pt}}$ = average travel cost in tolled route during peak period (pesos/vehicle)
$\boldsymbol{c_{ot}}$ = average travel cost in tolled route during off-peak period (pesos/vehicle)
$\boldsymbol{P_p}$ = trip price during peak period (pesos/vehicle)
$\boldsymbol{P_o}$ = trip price during off-peak period (pesos/vehicle)

4.10 Solve the Congestion Price

The congestion price can be easily computed after applying Newton's method. As presented in Eq. (13), the toll is just the difference between the optimal price and average cost

As the values were provided by SAS in the previous step, we were able to compute for the Pareto-efficient toll for each period by using Eq. (13) which is getting the difference between the optimal trip price (P) and its corresponding average cost (c).

Therefore we have the following toll rates:

$\boldsymbol{Toll_p}$ = toll rate for tolled route during peak period
= $P_p - c_{pt}$
= 21.2764 – 13.6458
= 7.6306 pesos

$\boldsymbol{Toll_o}$= toll rate for tolled route during off-peak period
= $P_o - c_{ot}$
= 81.1329 – 75.9033
= 5.2296 pesos

The toll fees stated above are the Pareto-efficient congestion tolls resulting from our study. Apparently, $Toll_p$ is higher as compared to $Toll_o$ since the demand for road use during peak period is higher.

5. CONCLUSION

Traffic congestion—inevitable in certain roads and at certain times of the day, is a problem taken for granted by authorities. Currently, the Philippines is using road pricing schemes such as toll ways (i.e., SLEX and NLEX) wherein a fixed amount is charged at any time of the day. The continual presence of an excess of people clustered in a certain road at a particular time (i.e., peak periods) despite extensive toll systems proves its ineffectiveness in solving traffic congestion.

Since congestion pricing has never been implemented or tested in the Philippines, our study offers a new perspective in the road pricing mechanisms in the country. In addition to this, it also serves as a guide as to how congestion pricing can be implemented via the estimation of the congestion toll. Given our results in the small scale trial in the Nichols to Merville Exit area, the significant price differential is very obvious as the supposed Pareto-efficient congestion toll is 75% less than the actual toll charge in SLEX. This shows that the actual toll charges do not reflect the true economic costs of road usage and are not welfare enhancing for the consumers. It is important to note that since SLEX is not privately owned, the toll charge currently imposed is for the purpose of road maintenance, rather than the recovery of private investments.

However, the Pareto-efficient congestion toll obtained through the small scale demonstration cannot be used for policy implications due to the limitations outlined at the beginning of this paper. These results are not accurate or adequate to be used for any generalizations (i.e., values are not absolute) but these values only serve as a proof that there is indeed room for improvement in the current pricing policies imposed in the country.

There are four major issues that must be addressed to improve the study: (1) data accuracy, (2) value of travel time estimation, (3) exclusion of maintenance costs, and 4) implication on other road networks.

For the data accuracy issue, there are a couple of factors to focus on. First is the income variable. Income has always been a confidential information, making it difficult to obtain with accuracy since respondents have a tendency to understate their income or not even bother to give it out at all. Second, the number of respondents obtained must be significantly improved if it is aimed to be fit for imposing new road pricing policies. Thus, the respondents collected must represent a good sample size of the whole population involved in the planned policy change. Third, the manual counting technique could still be improved to promote efficiency in the larger scale through the use of electronic counters and other more sophisticated technologies. Lastly, the field testing of the travel time must be done in a more scientific and accurate manner by performing the said procedure repeatedly at different days of the week.

Second, for the value of travel time estimation, it would be better if it could also capture other vehicle usage costs other than gasoline expense and toll fee, if applicable. Addressing this would ensure that the value of travel time obtained would be more precise as other costs are included in its computation process. Then, the value of travel time would more accurately predict the Pareto-efficient toll price.

Third, the costs that need to be considered in obtaining the Pareto-efficient congestion price must be comprised of those that would have an effect on demand for road use- such as gasoline expense and schedule delay costs as applied in this study. As such, the cost for road maintenance should not be incorporated for the simple reason that the government already allocates a certain portion of its tax revenues for infrastructure development specifically road maintenance- accounting for this cost in congestion pricing would entail double taxation which is not economically acceptable. However this claim of ours could be verified by future researchers.

Lastly, in assigning a congestion price on a particular area, its implication on the post area must be considered as well because of the possibility that the elimination of the congestion problem on one particular area would come at the expense of another. In this kind of situation, congestion is merely shifted from one area to another so in turn overall welfare is not attained. This problem is likely to occur when dealing with expressways wherein the entire road is subdivided into several toll gates and junctions.

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APPENDIX

Map of Nichols to Merville Exit Area