Predictive Distance-based Toll Optimization Under Varying Demand Levels

[1]Vinh-An Vu, [2*]Antonis F. Lentzakis, [2]Ravi Seshadri, [3]Gary Tan, [4]Moshe Ben-Akiva

1.Relativ, Tokyo, Japan
2.Future Urban Mobility IRG, Singapore-MIT Alliance for Research and Technology, Singapore
*email: antonios@smart.mit.edu
3.School of Computing, National University of Singapore, Singapore
4.Intelligent Transportation Systems Lab, Massachusets Institute of Technology, USA

Abstract

Real-time network control strategies such as congestion tolling are widely used for traffic congestion mitigation in urban transportation networks. Advances in Global Satelite Navigation System technology have led to increasing interest in distance- or usage-based tolling as an effective alternative to traditional facility-, cordon- and area-based tolling that typically rely on fixed infrastructure. We propose a framework for predictive distance-based toll optimization under variable demand. Given a set of charging zones, tolling function parameters are optimized using a simulation-based Dynamic Traffic Assignment (DTA) model operating within a rolling horizon scheme. Predictive optimization is integrated with the guidance information generation. Behavioral models capture drivers' responses to the tolls in terms of trip cancellation, mode, route and departure time. Evaluation of the proposed framework and solution algorithm, using the real-world Expressway network of Singapore, demonstrates the effectiveness of distance-based toll optimization in improving total social welfare compared to a traditional tolling scheme.

Keywords: distance-based road pricing, dynamic toll optimization, real-time traffic management

Introduction

Traffic congestion is a pervasive problem world-wide resulting in significant costs to the commuter, economy and environment. According to the Victoria Transport Policy Institute's Urban Mobility Report (UMR) (1), congestion was estimated to waste 5.5 billion hours of time delay and 2.9 billion gallons of fuel in urban areas of the United States between 2000 and 2010. The UMR predicted that congestion cost will increase from $121 billion (in 2011) to $199 billion (in 2020). Mitigating congestion is always a high-priority task in any transportation networks to enhance the network reliability, driver's comfortability and traffic safety. Road pricing is an important approach for congestion mitigation that encourages travelers to adjust all aspects of their behavior: number of trips, destination, mode of transport, time of day, route, and so on. Facility-based and area-based pricing typically depend on physical infrastructure such as gates or gantries to detect when drivers enter or leave the tolled area. Unfortunately, if there is a change in the charging facilities/areas, physical gantries are not so easily relocated. They also ignore the distance travelled within the tolling zone resulting in inequitable tolls for journeys of different lengths. The caveats associated with facility-/area-based pricing and the advancement of Global Satelite Navigation System technology have generated interest in usage-based tolling schemes wherein charges vary in terms of distance-traveled, time spent on traveling or time spent in congestion According to (2), time-spent-in-congestion-based pricing outperforms distance and time-based pricing because it achieves the greatest increase in network speeds. There is concern, however, that tolls based on time spent traveling and time spent in congestion would be unpredictable, and evidence shows that they potentially encourage unsafe driving (3). Distance-based pricing bypasses said concern while still solving the issues present in facility-/area-based pricing, such as inflexibility regarding gantry relocation and inability to charge users in an equitable manner. This has led to distance-based pricing becoming an area of increasing interest in both theory and practice. It was directly tested in the London study (4) and recently, Singapore has been in the process of distance-based pricing implementation with tender awarded in 2016 (5). Due to the increasing significance of distance-based road pricing in traffic network management and operations, this paper presents a distance-based road pricing strategy optimization framework which generates dynamic, predictive road pricing strategies together with traffic guidance in the context of varying demand levels.

Framework and Algorithm Description

In this section, we describe the framework, as well as the predictive distance-based toll optimization problem and the proposed algorithmic solution.

Framework

The framework for predictive distance-based toll optimization is using DynaMIT2.0 - a simulation-based Dynamic Traffic Assignment (DTA) system developed at the MIT Intelligent Transportation Systems Lab, (6,7). DynaMIT2.0 consists two main modules: state estimation and state prediction operating in a rolling horizon scheme. The state estimation module integrates real-time data obtained from traffic surveillance system, other information accessible in the historical database, the distance-based tolling zone definition and the translated demand/supply pattern from scenario analyzer to estimate the current network state through the complex demand-supply interactions. The state prediction module predicts traffic conditions over the prediction horizon and generates consistent guidance information, which will be disseminated to the travelers during the next roll period. The control strategy optimization and guidance generation process in DynaMIT2.0 is extended to optimize distance-based tolls. Within this process, the optimization module generates a series of candidate tolling function parameters which are to be evaluated on the basis of the desired objective. The state prediction and guidance generation module takes as input a candidate solution along with an initial guidance and predicts the future network conditions through the demand-supply simulators. This process yields simulated travel times, which will be combined with the previous guidance to generate an updated guidance, and the process continues iteratively until convergence. At this point, the generated guidance is considered consistent and the predicted network performance is used by the optimization module to evaluate the specified objective function. Based on the evaluated objective function value, the optimization module will generate a new set of control strategy candidates and the procedure will continue until optimality or a pre-specified set of termination criterion have been achieved.

Problem Description

The transportation network is represented as a directed graph $G = (N,A)$, where N represents the set of n network nodes and A represents the set of m directed links. Let L be the number of charging zones in the network G. Each charging zone l is defined as a subset of A, i.e. $\forall l \in \{1,...,L\}, A_l \subseteq A$, and is associated with a tolling function $\phi_l(\theta_l^t, D_l)$ that maps the distance traveled within zone l, D_l to the toll amount, and θ_l^t is a vector of tolling function parameters in time interval t. The toll payable within any charging zone is assumed to be bounded, i.e $\tau_{LB} \leq \phi_l(\theta_l^t, D_l) \leq \tau_{UB}, \forall l = 1,2...,L$.

Let Δ be the the size of the state estimation interval (typically 5 minutes) and $H\Delta$, the length of the prediction horizon. Without loss of generality, we assume that the optimization horizon (the future period over which we wish to set the tolling function parameters) is the same as the prediction horizon. In addition, assume that the tolling function parameters are fixed over time intervals of size Δ and that the tolling intervals are aligned with the estimation intervals of the DTA system. Consider an arbitrary estimation interval $[t_0 - \Delta, t_0]$, let $\theta^h = (\theta_1^h, \theta_2^h ... \theta_L^h)$ represent the vector of toll function parameters for all charging zones for the time period $[t_0 + (h-1)\Delta, t_0 + h\Delta]$ where $h = 1,...,H$. The vector of toll function parameters for the current optimization horizon is thus given by $\theta = (\theta^1, \theta^2, ..., \theta^H)$.

Consider the collection of vehicles $v = 1,...,V$ on the network during the prediction horizon $[t_0, t_0 + H\Delta]$. Let the travel time of vehicle v be represented by tt^v and the predictive guidance by $\mathbf{tt}^g = (\mathbf{tt_i^g}; \forall i \in A)$, where $\mathbf{tt_i^g}$ represents a vector of the time dependent link travel times (guidance) for link i . Note that the vehicle travel times $\mathbf{tt} = (tt^v; v = 1, ..., V)$ are the result of the state prediction module of DynaMIT and thus cannot be written as an explicit function of the toll function parameters and predictive guidance. Thus, we characterize the complex relationship through a single constraint that represents the coupled demand and supply simulators of DynaMIT as:

$$G(\mathbf{x^p}, \gamma^\mathbf{p}, \mathbf{tt^g}, \theta) = \mathbf{tt} \quad (1)$$

Where $\mathbf{x^p}$, $\gamma^\mathbf{p}$ represent the forecasted demand and supply parameters for the prediction horizon, and θ is the vector of tolling function parameters. The iterative procedure within the state prediction module ensures consistency between $\mathbf{tt^g}$ and $\mathbf{tt}$.

The response of users to the predictive distance-based tolls and travel time guidance is modeled at the pre-trip choice and en-route choice levels. The pre-trip choice model includes decisions of trip cancellation, mode, departure time and path and is formulated as a nested logit model. Thus, a driver may choose to change his/her habitual travel pattern (in response to the predictive guidance and tolls) in which case he/she may either change mode, cancel trip, change path or departure time, or a combination of the two.

The objective function for the optimization problem can be formulated from the consumers' perspective, producers' perspective or both. In this study, we adopt the objective of total social welfare (SW), defined as the sum of the consumer surplus and the producer surplus. Since we have simulated the choices of each traveler, the consumer surplus (CS) in this setting is simply the sum of the experienced utilities of each traveler. The producer surplus is the net toll revenue (TP) given by the total toll revenue (TR) minus the fixed costs (FC) and variable costs (VC). Thus, $SW = CS + TP = CS + (TR - FC - VC)$. Fixed costs are assumed to be 0. In addition, the variable cost component is assumed to be a portion of the total collected toll revenue with factor $\alpha < 1$. The total social welfare is thus given by:

$$\begin{aligned} SW &= CS + TP \\ &= CS + (TR - FC - VC) \\ &= \sum_{v=1}^{V} \frac{\cup^v}{|\beta_c^v|} + \left[(1-\alpha) \times \sum_{v=1}^{V} tc^v \right] \end{aligned} \quad (2)$$

The absolute value of β_c^v is used to express the consumer surplus in dollar equivalents. The dynamic distance-based toll optimization problem (DDTOP) in our context is formulated as a non-linear programming problem given in Equation 3. The decision variables are the vector of tolling function parameters for the optimization horizon period. The objective function is the total social welfare. The constraints are the DynaMIT system and upper and lower bounds on the toll values.

$$\begin{aligned} &\mathbf{DDTOP} : \max_{\theta} \left[\sum_{v=1}^{V} \frac{\cup^v}{|\beta_c^v|} + (1-\alpha) \times \sum_{v=1}^{V} tc^v \right] \\ &\mathbf{s.t.} \\ &\quad G(\mathbf{x^p}, \gamma^\mathbf{p}, \mathbf{tt^g}, \theta) = \mathbf{tt} \\ &\quad \tau_{LB} \leq \phi_l(\theta_l^h, D_l^v) \leq \tau_{UB}, \forall v = 1, 2, ..., V; l = 1, 2..., L; h = 1, 2, ..., H \end{aligned} \quad (3)$$

Solution

Due to the highly non-linear nature of the objective function of the DDTOP, with no guarantee of convexity, as well as the obvious difficulty to define closed analytical expressions that represent the drivers' dynamic route choice decisions as a function of the overall network traffic state and the developed tolling strategy, we decided to adopt heuristic-based algorithms that could provide near optimal solutions.

In the current implementation, we adopt a Genetic Algorithm (GA) approach to optimize the parameters of

distance-based tolling functions. The algorithm starts with a random population of N control strategy individuals, which form the initial population or parent population. Each control strategy individual is a vector of distance-based toll function parameters for different road pricing zones in the network during the current optimization horizon: $\theta = (\theta^1, \theta^2, ..., \theta^H)$. The Optimization Module then sends this population of control strategies to the State Prediction module of DynaMIT for evaluation with the predefined objective function. The strategies in the initial population is then ranked based on the values of objective function (in our case, the total social welfare). From this N-individual parent population, genetic operators (such as tournament selection, SBX crossover, polynomial mutation) are applied to generate another N-individual child population. The newly generated children are then evaluated with DynaMIT2.0 State Prediction. After that they are merged with the parent population to form a bigger population of $2N$ individuals and out of which, N best individuals are selected to be the parent population for the next generation. The algorithm iteratively moves on until some stopping conditions are met. The stopping condition could be the computation budget in term of time, the number of generations/iterations or the minimum improvement in the objective function.
In order to speed up the optimization, parallel computing is employed in which the evaluations of different control strategy individuals are conducted in parallel, each in one processing unit. This could tremendously bring the execution time closer to real-time performance.

Experiments and Results

Non-adaptive cordon-based tolling strategy is a very common tolling scheme in many cities due to its user-friendly nature. Hence, this section is dedicated to compare the performance of adaptive distance-based tolling strategy against the one of non-adaptive cordon-based. Moreover, this performance comparison is done under different network concentration by varying the level of network demand. Besides the base demand with 200K vehicles, two more levels of demand are benchmarked including the *low* level (uniformly reducing number of vehicles to 100K vehicles) and the *high* level (uniformly increasing number of vehicles to 300K). Figure 1 summarizes the results. As shown in the Figure, distance-based tolling strategy outperforms non-adaptive cordon-based tolling strategy in achieving the objective function. The total social welfare (SW) when distance-based tolling strategy is activated improves upto 2.85% compared to the non-adaptive tolling strategy. In addition, the Figure shows that the improvement of the objective function is higher when increasing the demand. Low demand achieves smallest improvement while high demand achieves the largest improvement. This happens because when the network is more congested, the choices made by the drivers will have more impact to the overall network conditions.
Even though travel time (TT) is not the main objective function but it is an important metric to assess the efficiency of the network. It turns out that distance-based tolling strategy also yields a very favorable output of average travel time. For all the demand levels, distance-based tolling strategy reduces the average travel time of trips compared to the non-adaptive scenario. And similar to total social welfare, the improvement in travel time is also proportional to the demand levels. The reduction in travel time shows the effectiveness of distance-based tolling strategy in managing congestion even though it is not the direct objective of the system.

Conclusions

In this paper, we presented a framework for predictive distance-based toll optimization under varying demand levels. Given a set of charging zones, tolling function parameters are optimized using a simulation-based DTA model operating within a rolling horizon scheme. Predictive optimization is integrated with the guidance information generation. Behavioral models capture drivers' responses to the tolls in terms of trip cancellation, mode, route and departure time. Evaluation of the proposed framework and solution algorithm, using the real-world Expressway network of Singapore, demonstrates the effectiveness of distance-based toll optimization in improving total social welfare compared to a traditional tolling scheme. Concretely, we can observe total social welfare improvement of 2.64%, 2.7% and 2.85% for Low, Base and High demand levels respectively. Especially for High demand levels, the collateral benefit to travel time savings is significantly higher than for Low and Base demand levels. In future work, we aim to investigate the effects of other factors, such as the

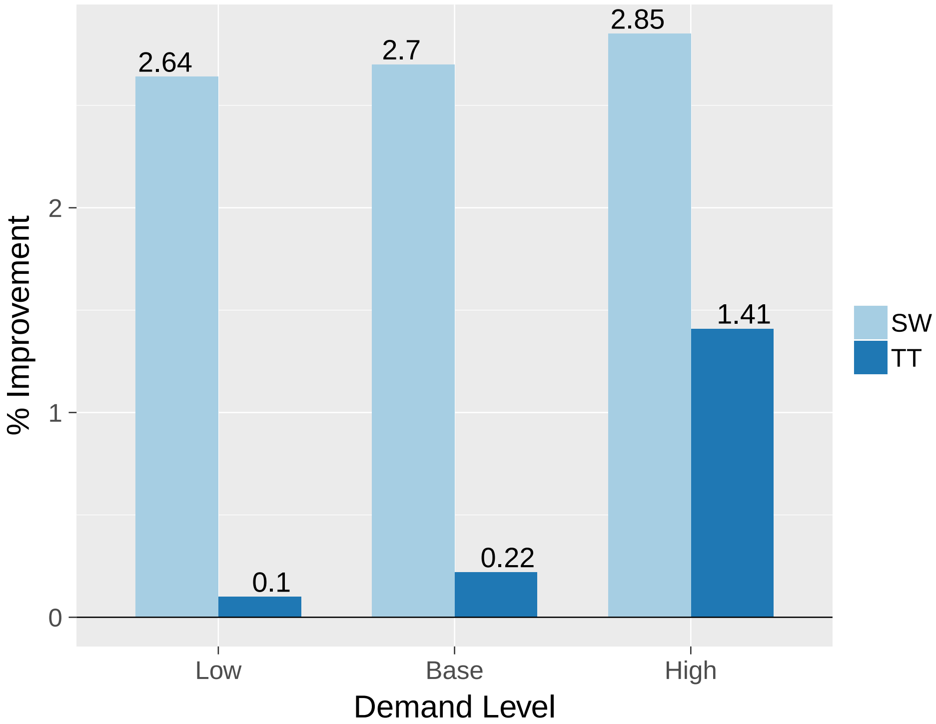

Figure 1 – Overall Performance Improvement of Adaptive Distance-based Tolling over Non-Adaptive Cordon-based Tolling with Varying Demand

number of zones and different tolling functions.

References

1. Litman, T., (2014). Congestion Costing Critique Critical Evaluation of the Urban Mobility 2014 Report. Victoria Transport Policy Institute.

2. Smith, M.J., May, A.D., Wisten, M.B., Milne D.S., Van Vliet, D. and Ghali, M.O., (1994). A comparison of the network effects of four road-user charging systems, Traffic Engineering and Control, vol. 38, no. 5, pp. 311-315

3. Bonsall, P. and Palmer, I.A., (1997). Do time-based road-user charges induce risk-taking? - results from a driving simulator, Traffic Engineering and Control, vol. 38, no. 4, pp. 200-203

4. Richards, M., Gilliam, C. and Larkinson, J. (1996). The London congestion charging research programme: 1. The programme in overview, Traffic Engineering and Control, vol. 37, no. 2, pp. 66-71

5. LTA, (2016). Tender Awarded to Develop Next Generation Electronic Road Pricing System, https://www.lta.gov.sg/apps/news/page.aspx?c=2&id=0bd76988-3c70-4b1f-9b68-65bb7fb47d56

6. Ben-Akiva, M., Koutsopoulos, H.N., Antoniou, C. and Balakrishna, R. (2010). 10-Traffic Simulation with DynaMIT, in J. Barcelo (ed), Fundamentals of Traffic Simulation, New York

7. Lu, Y. Seshadri R., Pereira, F., O'Sullivan, A., Antoniou, C. and Ben-Akiva, M. (2015). DynaMIT2.0: Architecture design and preliminary results on real-time data fusion for traffic prediction and crisis management, in Proceedings of IEEE 18th International Conference on Intelligent Transportation Systems, Las Palmas de Gran Canaria, Spain, pp. 2250-2255