Designing Dynamic and Personalized Travel Incentives for

Transportation Network Efficiency

Yanshuo SUN[1] and Chenfeng Xiong[2*] and Lei Zhang[3*]

[1]Ph.D., Department of Civil and Environmental Engineering, University of Maryland, 1173 Glenn Martin Hall, College Park, MD 20742; email: yssun@umd.edu
[2]Assistant Research Professor, Department of Civil and Environmental Engineering University of Maryland, 1173 Glenn Martin Hall, College Park, MD 20742; email: cxiong@umd.edu
[3]Herbert Rabin Distinguished Professor, National Transportation Center, Department of Civil and Environmental Engineering, University of Maryland, 1173 Glenn Martin Hall, College Park, MD 20742; email: lei@umd.edu

Abstract

This paper explores an emerging strategy of transportation demand management, where dynamic and personalized incentives are transferred to travelers in order to influence their travel choices toward a more socially desirable state. We first show that user-based incentives are futile under the complete information and full rationality assumptions, as other travelers instantaneously fill up the room left by incentivized travelers, thus canceling any marginal benefit improvements. Therefore, day-to-day traffic dynamics models are adopted, where commuters update their perceived travel time through trying and learning, based on which choices are made. A mathematical programming model is proposed for the system operator to design individually customized incentives on a daily basis. The effectiveness of travel incentives in improving the system benefits in the short and long runs is explored through numerical analyses. We identify a paradox that increasing incentive limits do not necessarily improve the system efficiency in the long run, due to probabilistic responses of travelers, i.e., we can influence while not control travelers' choices.

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Introduction

This study explores the effectiveness of an emerging strategy – dynamic and personalized incentivization – in improving the transportation system efficiency through influencing travelers' choice behaviors. Many transportation demand management measures have been proposed to move from a suboptimal user equilibrium state resulting from selfish travel decisions to a more socially desirable outcome, such as congestion pricing *(1)* and tradable credit scheme *(2)*, among others. Economists advocate congestion pricing because they believe the social efficiency is achieved if travelers bear the costs they impose on others. There are several types of congestion pricing schemes, most of which are facility-based. For example, users who traverse a particular road link or a designated cordon need to pay tolls. In the proposed tradable travel credit scheme, credits are distributed by the government to all eligible travelers; travelers are charged based on their use of a roadway link; excessive credits can be traded in a free market. Due to equity issues and political resistance *(3)*, these two instruments are implemented in only a few cities in the world. Instead of applying tolls or redistributing credits, government agencies are increasingly interested in designing and implementing various incentive programs. For example, the Commuter Connections Program of the National Capital Region Transportation Planning Board (TPB) would offer a financial benefit to commuters if they were willing to shift their departure times from peak hours to off-peak hours *(4)*. The Georgia Department of Transportation offers \$5 a day, up to \$150, if commuters switch to alternative commute modes, such as carpooling, walking, and biking *(5)*.

Nonetheless, these incentives are mostly long-term and rather fixed, due to a lack of real-time information provision and the absence of dynamic allocation methods. While static incentives could positively influence individuals in the long run, incentives can become much more effective when they are optimized for each person and for each trip dynamically based on the transportation demand-supply dynamics.

The contribution of this study is thus to develop a systematic modeling framework for dynamic and personalized travel incentives with the objective of maximizing the system-wide travel efficiency (e.g., minimizing the total travel time). An important characteristic of the proposed incentivization scheme is analyzed first, followed by a description of the overall modeling framework and research outcomes.

Methodology

Implications of user-based incentivization

The complexities brought by user-based incentives can be illustrated with the following example. One unit of traffic travels from the origin to the destination through either path 1 or path 2. The monetary delay cost of a path is a function of the path volume, which is $s_1(x_1) = x_1^2 / 3$ for path 1 and $s_2(x_2) = 2x_2 / 3$ for path 2. At the user equilibrium (UE), both paths have the same delay, we obtain $x_1^{UE} = 0.732, x_2^{UE} = 0.268$. The total delay is 0.1786. Alternatively, we minimize the total delay cost and obtain the system optimal (SO) flow assignment, $x_1^{SO} = 0.667, x_2^{SO} = 0.333$. The total delay is 0.1728.

It is clear that path 1 is over utilized at UE relative to the SO assignment. Therefore, we can design a tolling scheme where each traveler using path 1 needs to pay a certain toll. It is understandable that facility-based tolls can maintain system-optimal traffic flows, because no travelers would switch their choices once tolls are properly set. Likewise, *facility-based incentives* can be used to attract more traffic to path 2 and each traveler using path 2 can receive incentives. In this case, the SO traffic flows can be maintained as long as incentives are appropriate.

Nonetheless, we note that facility-based incentives and user-based incentives are different. To move from UE toward SO, 0.065 unit of traffic should be shifted from path 1 to path 2. To compensate for the delay increase, incentives in the amount of 0.065*(0.222-0.1786) = 0.00282 are needed, where (0.222-0.1786) is the monetary delay increase for one unit of traffic. Since 0.00282+0.1728 < 0.1786, the financial monetary transfer seems to be justified. However, the sustainability of the SO flow pattern obtained after applying user-based incentives depends on one critical assumption about preexisting traffic on path 2. Note that after 0.065 unit of traffic is moved from path 1 to path 2, the congestion level of path 1 decreases and the existing traffic volume on path 2 experiences increased delay due to the addition of traffic to path 2.

In the traffic equilibrium studies, complete information is assumed so that travelers have the complete spatial knowledge and more importantly travelers are assumed to be able to observe other travelers' moves (or choices). Two relevant scenarios are analyzed as follows:

Scenario A: preexisting traffic on path 2 will not shift to Path 1, if it is assumed that preexisting traffic cannot perceive the delay increase or they would not switch routes due to inertia or other reasons. In other words, *the interaction between incentivized travelers and other travelers is neglected*. Then, the SO flow pattern is sustainable. However, Scenario A holds only when the delay increase is negligible or the number of incentivized travelers is insignificant as compared to the total number of travelers.

Scenario B: preexisting traffic on path 2 can switch to path 1 to minimize their cost. Then, the SO flow pattern is not sustainable and it is expected that the same amount traffic will be shifted from path 2 to path 1 so that the delay levels of two paths are equal and the same delay level replicates the delay level prior to applying any incentives. If traffic is homogeneous, it is expected that the flow at the new UE is same as the original UE without any financial incentives. In this case, incentives are not justified as they will not reduce the system delay at all.

Thus, we conclude that under the complete information and perfect rationality assumptions, user-based incentives are futile under the complete information and full rationality assumptions, as other travelers instantaneously fill up the room left by incentivized travelers, thus canceling any marginal benefit improvements.

We depart from these behaviorally unrealistic assumptions and consider a day-to-day travel evolution framework rather than equilibrium models to model how commuters update their knowledge about their choices, make choice decisions, and respond to monetary incentives on a periodic basis.

Overall modeling framework

The overall modeling framework involves two day-to-day traffic dynamics models (shown in Figure 1), only the latter of which involves incentives. At the beginning of each day, commuters simultaneously make choices based on their own beliefs about all choices, without knowledge of their opponents' decisions. After all commuters have made their decisions, the network flow pattern is formed and a commuter obtains a new observation of the attribute of the chosen choice. Based on the new observation, a commuter updates his/her belief about the chosen choice, while beliefs about other unchosen choices remain the same, because no new information is acquired. The updated beliefs are used as the basis for decisions on the next day.

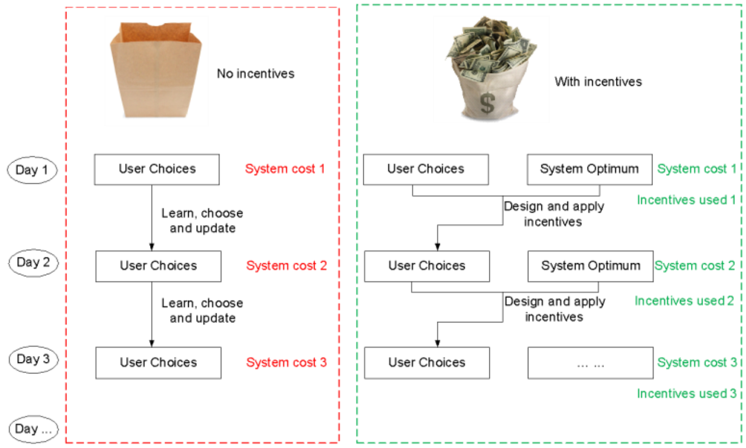


Figure 1: Overall modeling framework

In another case involving incentives, the system operator determines the amount of incentive to be transferred to a traveler if a certain option is chosen. Since the incentive is time-specific (day-specific), option-specific and traveler-specific, the incentive is considered dynamic and personalized. Incentives can affect travelers' beliefs about systematic utilities of travel options, thus influencing their travel choices. Nonetheless, due to the existence of random utility, the system operator cannot know exactly which option will be chosen by a traveler while optimizing incentives. Therefore, in the incentive design phase, the system operator can only predict the choice probability associated with each option for each traveler and minimize expected total travel time, subject to the incentive budget limit in the design phase. The final choice is observed only after a traveler finishes the trip, upon which the corresponding incentive is transferred. Similarly, after a trip is finished, a traveler updates his/her belief about the chosen option.

After a certain period, results from two traffic dynamics models are compared to see whether travel incentives can reduce the system cost. Although the incentive design principal is that on each day, the system cost saving exceeds the incentives applied, it is not immediately clear whether such incentives are justified over an extended period. We note that monetary incentives affect travelers' beliefs, thus affecting their choice evolution dynamics.

Day-to-Day Choice Dynamics

The set of commuters (or travelers, interchangeable throughout this paper) is denoted as I and a commuter is denoted as $i \in I$. Each commuter chooses one trip option $j \in J$, where J is the set of all trip options. The option is generic, which can be route or departure time, depending on the context. A day is denoted as $k \in K$, where K is the planning horizon. To model the interactions among travelers' choices, the travel time of option j depends on the number of travelers (i.e., volume, denoted as f_j^k) choosing it, as follows:

$$\tau_j = S_j(f_j^k), \forall j \tag{1}$$

where $S_j(\cdot)$ is a continuously differentiable and nondecreasing function of volume f_j^k.

The belief about option j's travel time of commuter i on day k is denoted as t_{ij}^k, and the incentive to be transferred to traveler i when the option j is selected is x_{ij}^k. Given t_{ij}^k and x_{ij}^k, traveler i selects option j with the highest utility U_{ij} among all alternatives . The utility function is written as:

$$U_{ij} = -v_i t_{ij}^k + x_{ij}^k + \varepsilon_{ij}, \forall i, j \tag{2}$$

where v_i is the value of time of traveler i and ε_{ij} is the independently, identically distributed random utility to capture the effect of all unobserved factors on choices of traveler i. For convenience, it is assumed that ε_{ij} follows a Gumbel distribution with location parameter $\mu = 0$ and scale parameter β_i, which do not change over time. Then, Equation (3) is used to predict the probability for choosing option j by commuter i on day k:

$$p_{ij}^k = \frac{\exp(\beta_i(-v_i t_{ij}^k + x_{ij}^k))}{\sum_{j \in J} \exp(\beta_i(-v_i t_{ij}^k + x_{ij}^k))}, \forall i, j, k \tag{3}$$

A binary decision variable $y_{ij}^j, \forall i \in I, j \in J, k \in K$ is introduced to indicate whether traveler i selects option j on day k. If option j is chosen by traveler i on day k, $y_{ij}^k = 1$; it is 0, otherwise. Once an option is chosen by each commuter, the realized flow pattern is observed, which determines the travel time of each option, according to Equation (1). Then, commuters update their beliefs about their chosen options with the following formula:

$$t_{ij}^{k+1} = \theta_i \tau_j (Y^k) + (1 - \theta_i) t_{ij}^k, \forall i, j, k \tag{4}$$

where $\tau_j(Y^k)$ is the travel time of option j on day k, which depends on choices by all travelers Y^k.

In Equation (4), the positive parameter θ_i between 0 and 1 is used to model the forgetfulness of the commuter. When $\theta_i = 0$, the newly observed information $\tau_j(Y^k)$ does not affect the belief; when $\theta_i = 1$, the commuter forgets all past experience once a new observation becomes available. In practice, $0 < \theta_i < 1$.

If an option is not chosen, no updated information about this option is available and the belief about such an option remains the same, i.e., $t_{ij}^{k+1} = t_{ij}^k, \forall i, j, k$. This day-to-day traffic dynamics model captures how travelers learn from past experience and adapt their decisions according.

Incentive allocations

On a given day k, the system operator designs incentives by solving the following mathematical program:

$$\min_{x_{ij}^k} \sum_{j \in J} \left(f_j^k \tau_j \left(f_j^k \right) \right) \tag{5}$$

s.t.

$$f_j^k = \sum_{i \in I} p_{ij}^k, \forall j \in J \tag{6}$$

$$p_{ij}^k = \frac{\exp(\beta_i(-v_i t_{ij}^k + x_{ij}^k))}{\sum_{j \in J} \exp(\beta_i(-v_i t_{ij}^k + x_{ij}^k))}, \forall i \in I, j \in J \tag{7}$$

$$\sum_{i \in I} \sum_{j \in J} x_{ij}^k \le B^k \tag{8}$$

$$x_{ij}^k \geq 0, \forall i \in I, j \in J \tag{9}$$

The objective (5) is to minimize the (expected) total travel time. Equation (6) defines the expected volume of each option. Equation (7) defines the choice probability. Constraint (8) specifies the incentive budget in the design stage and constraint (9) is the nonnegative constraint. It is noted that for a traveler, multiple options can be associated with positive incentives, while the traveler can only choose one option. The actual incentives transferred to travelers should be smaller than B^k.

After the optimized incentives are presented to travelers, each traveler selects one option that maximizes the traveler's random utility. After all travelers have finished their trips, the actual travel time is observed for each option and travelers update their beliefs accordingly. Due to the random responses of travelers to incentives, designed incentives are not necessarily taken by designated travelers. Therefore, the amount of incentives actually claimed should be less than the budget limit in the design stage.

Illustrative studies

A two-link network

Assume that 100 people need to travel from the origin to the destination on the network in Figure 2. Link performance functions are also specified in Figure 2. The value of time is distributed uniformly over the range [5, 10] $/hour. On the first day, each traveler's belief about a path's travel time is uniformly distributed over [0.1, 0.6] hours. Therefore, without any incentives, half of travelers are expected to travel on each path. At the system optimality, 2/3 should travel via Path 1 and the rest travel via Path 2. The total travel time is thus 100 * (2/3*1/3*2/3*2/3+1/3*2/3*1/3) = 0.1728 * 10^2 hours.

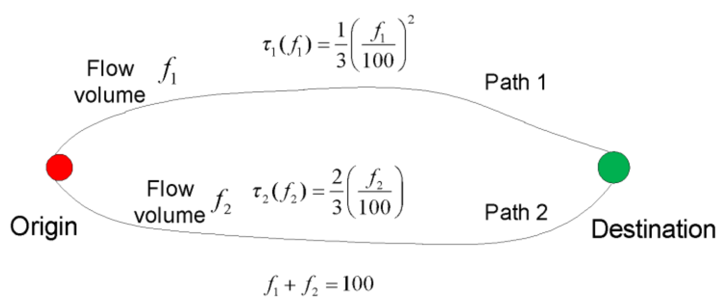


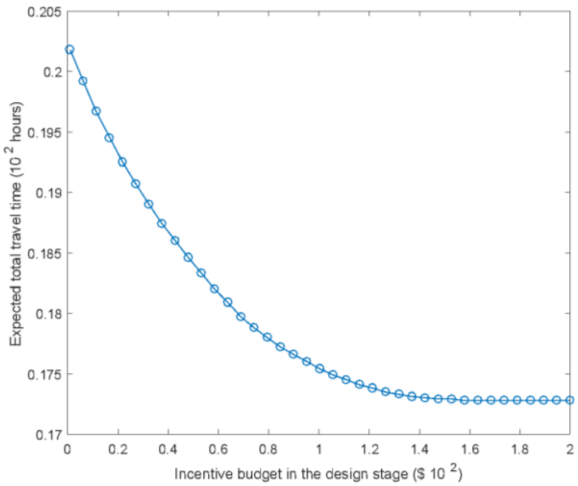
Figure 2: A sample network

Analysis for a single day

Figure 3 shows how the expected total travel time declines as the incentive budget increases. Computational tests also show that when the incentive budget is slightly larger than 1.5 * 10^2 $, the SO flow pattern is expected to be achieved (shown in Figure 4) and the total travel time is expected to drop to 0.1728 * 10^2 hours.

The saved travel time is (0.208-0.1728) * 10^2 hours, which is equivalent to 0.264 * 10^ $, assuming an average value of time 7.5 $/hour. When the transfer of public funds is costless, the social welfare is improving. However, when the cost of public funds is not zero, further tradeoff analyses are needed to justify the transfer of incentives.

We note that only expected values are shown in Figure 3 and Figure 4, while actual values depend on probabilistic responses of travelers to offered incentives.



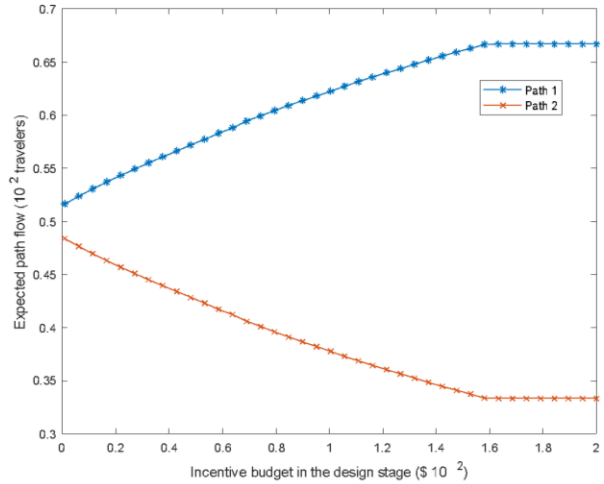


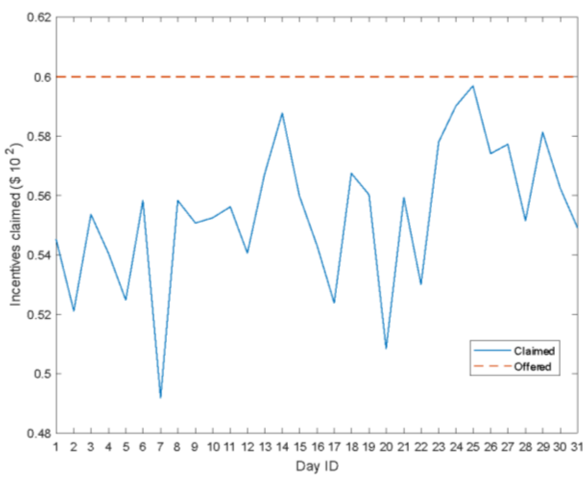
Figure 3: Expected total travel time vs incentive budget

Figure 4: Path flow volumes vs incentive budget

After incentives are optimized for each traveler and each option, travelers make their decisions based on incentives offered and travel time beliefs (Equation 3). After travelers have made their choices, incentives are claimed. It is understandable that not all incentives offered are claimed. In one computational test, \$ 100 are offered as incentives while only 71.18 \$ are claimed. The expected proportion of selecting path 1 is 65% while in the computation test, it turns out the actual proportion of selecting path 1 is 68%. It should be noted that all the deviations from the expectation are due to the randomness involved in travelers' route choices. We can influence, but not control travelers' route choices.

Analysis for a period

Figure 5 shows that not all incentives are claimed. The budget limit is \$ 0.6*10^2. Due to the randomness involved in the analysis, e.g., stochastic responses of travelers to incentives, the calculation is repeated ten times for each budget limit. Figure 6 clearly shows that in a certain range, increased budget limits could reduce the total travel time, while a threshold is reached, additional incentives in the design stage will not reduce the total travel time over an extended period. There are two possible reasons for this paradox: (1) random responses of travelers to incentives and (2) altered travel time learning processes due to incentives.



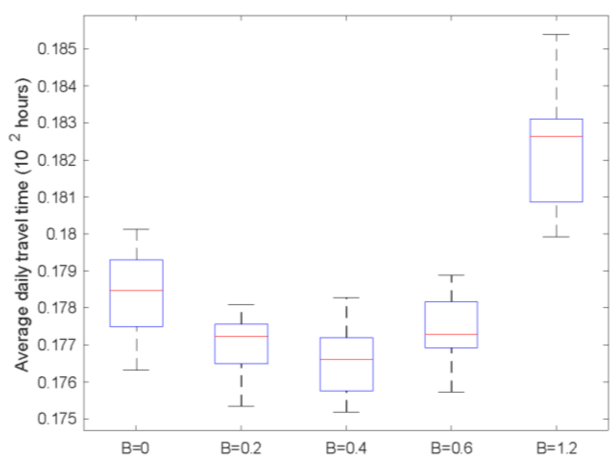


Figure 5: Evolutions of incentives claimed

Figure 6: Illustration of the paradox

Conclusions

This paper establishes a theoretical framework for analyzing the effect of dynamic and personalized incentives on travel behavior dynamics on a day-to-day basis. It also presents a practical method for allocating incentives so that the system operator knows how much incentive is allocated to which traveler to maximize the total system cost saving given a financial budget limit. Findings of this study could improve the planning and design of travel incentive programs in the real world.

Further work is need to explore whether the incentive allocation problem (5-9) could be solved to optimality noticing that this problem is nonconvex.

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