A Smart Mobility Platform to Analyze Fair Congestion Pricing with Traded Incentives and its VMT Impact

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The research project develops a modeling and analysis approach to evaluate the efficiency and fairness of a smart mobility platform that collects payments from travelers assigned to the shortest path between their origins and destinations and sends payments to travelers assigned to non-shortest paths, to adjust the "envy" they feel toward other's travel times, based on their values of time. The platform is tested in the realistic network of Los Angeles County, CA, centered on the I-10 freeway and modeled using Dynamic Traffic Assignment with mesoscopic traffic models. The results indicate that the platform will make the transportation network more efficient, resulting in a 13% increase of network space mean speed from 31 mph to 35 mph. While the extra benefits (i.e., negative of envy) for people in shortest path groups decrease after an envy-minimization price matching, the total envy of all travelers decreases to zero from $3,800 (measured in dollar terms for one hour of the morning peak), resulting in an envy-free situation and making the system fairer. All income groups benefit from this price matching scheme. Further research to integrate mode choice and transit into the modeling and analysis in the smart mobility platform will yield more holistic evaluations.		
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The Pacific Southwest Region UTC conducts an integrated, multidisciplinary program of research, education and technology transfer aimed at *improving the mobility of people and goods throughout the region.* Our program is organized around four themes: 1) technology to address transportation problems and improve mobility; 2) improving mobility for vulnerable populations; 3) Improving resilience and protecting the environment; and 4) managing mobility in high growth areas.

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Disclosure

The PI R. Jayakrishnan, Co-PI Michael Hyland, Post-doctoral scholar Daisik Nam, along with graduate student researchers Siwei Hu and Pengyuan Sun, conducted this research titled, "A Smart Mobility Platform to Analyze Fair Congestion Pricing with Traded Incentives and its VMT impact" at the Institute of Transportation Studies at the University of California Irvine. The research took place from January 1, 2021 to December 31, 2021 and was funded by a grant from the California Department of Transportation (Caltrans) in the amount of $81,342.00. The research was conducted as part of the Pacific Southwest Region University Transportation Center research program.

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Abstract

NOTE: Summary of research topic, approach, and findings; up to 200 words

The research project develops a modeling and analysis approach to evaluate the efficiency and fairness of a smart mobility platform that collects payments from travelers assigned to the shortest path between their origins and destinations and sends payments to travelers assigned to non-shortest paths, to adjust the "envy" they feel toward other's travel times, based on their values of time. The platform is tested in the realistic network of Los Angeles County, CA, centered on the I-10 freeway and modeled using Dynamic Traffic Assignment with mesoscopic traffic models. The results indicate that the platform will make the transportation network more efficient, resulting in a 13% increase of network space mean speed from 31 mph to 35 mph. While the extra benefits (i.e., negative of envy) for people in shortest path groups decrease after an envy-minimization price matching, the total envy of all travelers decreases to zero from $3,800 (measured in dollar terms for one of the morning peak), resulting in an envy-free situation and making the system fairer. All income groups benefit from this price matching scheme. Further research to integrate mode choice and transit into the modeling and analysis in the smart mobility platform will yield more holistic evaluations.

A Smart Mobility Platform to Analyze Fair Congestion Pricing with Traded Incentives and its VMT Impact

Executive Summary

Travelers in the Los Angeles region spend over 100 hours in congestion a year. Engineering practice and academic literature from diverse fields such as transportation, economics, and even human psychology, have devised several approaches to address congestion issues in the urban area. Currently, research and policies are arriving at the conclusion that pricing schemes hold the key to change the travelers' driving behavior and improve the efficiency of the transportation system. Monetary tolls are likely quite effective in changing drivers' behavior.

However, a significant proportion of newly constructed toll roads has failed to attract the expected number of drivers, resulting in underutilized road capacity (1). Furthermore, unfairness is also a primary barrier for tolls since drivers stick to their 'right' to free travel on urban roads (2). It makes congestion pricing policies politically difficult to implement in cities around the world (3). In addition, the current congestion pricing schemes are unclear about how the collected tolls are fairly/equitably distributed (4). As such, the goal of this study is to reform the traditional congestion pricing schemes and propose a fair and efficient smart mobility platform, by distributing revenues collected from tolls for the 'best' paths through the network to the other path groups.

In reality, travelers make their route choice decisions for their own benefit – they will choose their own shortest paths, which results in the User Equilibrium (UE) state, and hinders the possibility of reaching a more efficient state, System Optimal (SO) state. If some of the travelers yield to travel on non-shortest paths in a systematic way, the SO state could be achieved. However, routing travelers to longer paths without any compensation will generate unfairness among them. As such, this study proposes a smart mobility platform, in which some travelers are routed to non-shortest paths with compensation collected from the shortest path groups to minimize the unfairness.

To further define unfairness in the context of traffic operations, this research employs envy-theory, rather well known as a "fair cake-cutting problem" in Economics. It is introduced to transportation analysis here as a behavioral paradigm for fairness and efficiency. This study is to design a platform that achieves both system-wide efficiency and minimum envy among individuals.

The platform consists of two modules– the path-based SO dynamic traffic assignment (DTA) simulator module and the envy-minimization price matching module. The DTA simulator module includes a path-based gradient projection algorithm (5) to solve the DTA problem under SO state, while the envy-minimization price match module calculates the optimal pricing that minimizes each individual's envy. The majority research questions, and policy implications about the

platform addressed in this study include: (a) How well can the platform improve traffic condition, in terms of Vehicle Miles Traveled (VMT), Vehicle Hours Traveled (VHT), and space mean speed, etc? (b) How well can the platform address the unfairness problem? (c) Who will be active in and benefiting from this platform among different income groups, and different trip contexts?

To answer these questions, this study tests the proposed platform in a realistic network of Los Angeles County centered on the I-10 freeway, with morning peak demand input from the California Statewide Travel Demand Model (CSTDM). Simulation results illustrate that the network becomes less congested with the proposed platform. Compared with the dynamic user equilibrium (DUE) case, which can be regarded as a real-world situation, the VMT in the proposed platform is increased by 7% and the VHT decreases by 5%. It results in a 13% increase of network space mean speed from 31 mph to 35 mph. This study also finds that the proposed platform could make the system fairer and more satisfactory from the individual perspective. Although before the price matching, the proposed platform generates a great amount of envy among travelers, $3,800 (measured in dollar term), envy of all travelers is reduced to zero after the price match. However, in the DUE case (real-world situation), envy remains unchanged at $325.30. Compared with the DUE case where extra benefits for travelers remains at $857.54, the platform could generate extra benefits for travelers at $3,227.13 even after price matching. Moreover, the study finds that in terms of trip context, most of the travelers active in and benefiting from the smart mobility platform are the travelers moving through the analysis area, as opposed to those whose trips start and end within the analysis region. In terms of socio-economic characteristics, all income groups will benefit from this platform. Further research effort could be made to integrate the transit system into the modeling and analysis approach to support more holistic evaluations (and provide travelers a valuable alternative). Further impact analysis could also assess the vehicle ownership change brought by the proposed platform. Further detailed analysis could be done to analyze the impact this platform has on the marginalized groups.

Introduction

Travelers in the Los Angeles region spend over 100 hours in congestion per year, on average (The 100 Hours public engagement campaign, SCAG, 2019[1]). Engineering practice and academic literature from diverse fields such as transportation, economics, and even human psychology, have devised various approaches to reduce congestion. However, the underlying challenge associated with traffic congestion is that travelers optimize their own outcomes rather than those of the system. Notably, when it comes to the routes that travelers choose, when travelers optimize their own outcomes, congestion typically is the outcome.

Currently, related studies and policies tend to argue or conclude that pricing schemes hold the key to altering behavior such that travelers who optimize their own outcomes will change their behavior due to pricing such that the total system travel time is minimized. Monetary tolls are likely effective in changing drivers' behavior. However, a significant proportion of newly constructed toll roads have failed to attract the expected number of drivers, resulting in underutilized road capacity (1). Furthermore, unfairness complaints about pricing/tolls is a primary barrier to implementing any pricing schemes, since drivers tend to stick to their 'rights' on free travel on public roads (2). In fact, implementing congestion pricing is now primarily a political challenge (3,4), as opposed to a technical one.

Another important congestion pricing issue, which underpins part of the political challenge, is that it is often unclear whether the revenue collected from tolls are fairly/equitably distributed (4). This study proposes a smart mobility platform that reforms the traditional congestion pricing scheme by distributing payments collected from travelers on the "best" paths between an origin-destination pair to travelers on non-best paths between the same origin-destination pair. In other words, we propose a fair and efficient smart mobility platform where revenues collected from tolls are used to incentivize the other users who are willing to yield their shortest path. This platform would contribute to the redistribution of money to low-income people as a travel credit that they can use for other travel purposes.

The pricing mechanism in the smart mobility platform plays an important role in changing travelers' behavior, given that some travelers are more sensitive to the price than others. While most existing models and analysis methods assume that travelers are homogeneous in terms of their willingness-to-pay for travel time savings, this study proposes an agent-based modeling and analysis approach that incorporates heterogeneity in the value-of-time (VOT) across agents. Even for research based on heterogeneous assumptions, travelers are often categorized by averaging preferences (i.e., VOT) among different groups. This categorization simply breaks travelers into different reasonable sized groups, but doesn't treat each traveler with heterogeneity. Our research is to find optimum pricing where the individual level of envy is minimized by considering

[1] https://scag.ca.gov/100-hours

the heterogeneity of travelers. We employ envy-theory, well known as a “fair cake-cutting problem” in Economics as a behavioral paradigm for fairness analysis.

Studies on the individual level of optimization of transportation systems with such a scheme have been conducted at the Institute of Transportation at UC Irvine. Numerical examples in an Irvine, California network (personal vehicles only), simulated with a dynamic traffic assignment model, show that the proposed method can improve travel speeds on the I-405 and the I -5 by 8.3 % during the morning peak (5) . Moreover, the study shows that the proposed smart mobility platform can ensure an envy-free state by collecting payments from travelers on the shortest path between an origin-destination pair and sending payments to travelers on non-shortest paths. The current study applies a similar modeling approach in an even larger real-world network in Los Angeles County centered on I-10 freeway. The origin-destination demand in the LA County I-10 network is obtained from the California Statewide Travel Demand Model (CSTDM). Finally, the value of time (VOT) for each agent in the simulation is based on the recent research in a similar region of California (6).

Background and Literature Review

Review on Dynamic Traffic Assignment

Since the seminal DTA research proposed by Merchant and Nemhauser (7), there have been considerable advancements in DTA methods (8). Various DTA methodologies have been proposed, such as optimization models (7), optimal control models (9) and simulation-based models (10,11). Compared with the former two kinds of models which are applicable for small networks, the simulation-based models could be applied to solve DTA problems in realistic networks.

Several researchers have contributed to the studies on simulation-based DTA models from different perspectives. Mahmassani et al. use speed-density relationships in DYNASMART-X, a DTA model based on a mesoscopic simulation (12). Zhou and Taylor propose a mesoscopic traffic simulation approach and develop the traffic assignment package DTALite to simulate large-scale networks with millions of vehicles (13). Jayakrishnan et al. propose a DTA model with bi-level optimization framework and derive a link-cost function with respect to traffic loads, the number of vehicles present on a certain link, and solve the DTA model analytically (14). Later, Yang and Jayakrishnan solve the DTA model using a simulation-based approach with a microscopic model (15). Recently, Nam proposed a DTA model using a mesoscopic simulation that is analytically built into the DTA (5)which is used in this paper.

There are many solution algorithms to solve DTA problems. Gradient projection (GP) path-based algorithm, first proposed by Jayakrishnan et al. (16), is a feasible direction algorithm that operates directly in the path flow space. Later, Yang and Jayakrishnan adopt it to solve DTA problem with microscopic models (15). Gentile shows that GP algorithm can solve DUE models with splitting rates (i.e., turning movement fractions by destination) with high precision (17).

Nam adopts the GP algorithm to solve the Dynamically Allocated System Efficiency with Envy Minimization-Price Matching (DASEEM-PM) problem (5).

In this report, the agent-based framework in Nam is adopted to solve the DTA problem under SO condition (5). It is because the redistribution of collected payments from travelers on the shortest paths to those on non-best paths requires path-level DTA solution, which could be obtained from path-based DTA algorithm in Nam (5). Another reason is that the key component in the envy-minimization, peer-to-peer envy comparison, is conduct at the agent level. Therefore, the agent-based DTA framework in Nam is suitable for this study.

Review on Peer-to-peer supply exchange with pricing

Various theories have been proposed in the past to achieve system optimum condition—road pricing theory being a prominent example. This theory finds the optimum condition by implementing marginal travel costs, which enables a government entity to collect congestion tolls. The amount of toll is the difference between the marginal and average travel times on each link (18–20).

By assuming all travelers are participants, Yang and Wang conclude that the tradable credit scheme can guide traffic to have a social optimum pattern (21). Nie examines Yang and Wang's tradable credit scheme and focuses on how transaction costs affect the tradable mobility credits in both an auction market and a negotiated market (3). By realizing the fact that a tradable credit scheme is more controversial as an infringement of personal freedom than congestion toll, Nie examines how the government offers a proper price including a transaction cost (3). Nie and Nie and Yinapply the tradable mobility credit scheme to the departure time selection problem for managing rush hour traffic (22,23). Drivers not driving during the peak hour earn credits by contributing to congestion relief. Moreover, the participants driving during the peak hour need credits to drive. The participants who need more credits can purchase them in a trading market. A tradable credit scheme is a possible alternative to the conventional congestion toll when the credits are reasonably allocated to the participants. However, initial allocation of tradable credits among all travelers is another challenge (24). In addition, Nie pointed out that some people might be restricted to driving a credit-consuming road since they cannot purchase the credit with an affordable price (3). This might create another instance of unfairness, which should be carefully considered.

Efforts are made by researchers to navigate travelers to reach the SO state. Pan, et al. proposes proactive vehicle re-routing strategies (25). Recognizing that the system cannot force the drivers to select the longer path, they suggest several re-routing strategies to avoid congestion. Among them, the Entropy Balanced k Shortest Paths (EBkSP), which balance the traffic load with multiple paths, could meaningfully improve overall congestion. Liu et al. employs Pan, et al.'s EBkSP to develop a participatory navigation system, which is called "Themis" (26). Themis predicts future traffic flow and speed. This information is used to make people drive on less popular routes by showing a score. The score is calculated by considering the average estimated time of arrival and popularity of a route.

Many researchers argue that providing incentives will contribute to changing travelers' behavior (27–29). The relationship between incentives and tolls can be likened to the "Carrot or Stick" idiom. Findings in psychology literature, such as (30) and(4), show that an incentive scheme brings about better outcomes than punishment scheme like fee payment from travels. They also show that a reward scheme can be effectively used to manage travel demand from a survey test for "Spitsmijden (Dutch for peak avoidance)" in the Netherlands. They show that participants change their commuting schedule to avoid peak hour when they earn rewards.

In this study, the payments and incentives scheme are adopted to collect payments from travelers on the shortest path group and distribute them as incentives to those on the non-shortest path group. This scheme could compensate the envy generated from the individual routing strategy recommended by the proposed platform.

Problem Statement

Problem Description

The underlying problem that the smart mobility platform addresses is as follows.

Given:

- a set of travelers, each with a fixed origin, destination, departure time, and value of time; and
- a transportation network composed of links and nodes as well as a variety of link attributes including link length, free flow speed, jam density, number of lanes, etc.

Determine, for each origin-destination-departure time triad with at least one traveler:

1. the set of paths in the optimal set
2. the share (and number) of travelers on each path
3. the payments each traveler pays to and or receives from the smart mobility system

that (i) minimize total system travel time and (ii) ensure no traveler is envious of another traveler in terms of path travel time and payment sent/received.

Methodology

This section describes the models and solution methods to solve the problem described in the previous section. Effectively, the solution approach to solve the problem involves first solving the system optimal dynamic traffic assignment problem (SO-DTAP), which minimizes cumulative travel time throughout the entire network. The outputs of the SO-DTAP include the set of paths and the share (and number) of travelers on each path for every Origin-Destination-Departure Time (ODT) triad with at least one traveler. Given the outputs of the SO-DTAP the second part of the solution approach involves solving the problem of determining how much each traveler pays or receives in order to ensure no traveler is envious of another.

The remainder of this Methodology section describes the SO-DTA problem, model, and solution, as well as the fair allocation of supply through pricing problem, model, and solution.

System Optimal Dynamic Traffic Assignment Problem (SO-DTAP)

System Optimal Dynamic Traffic Assignment Problem is introduced in this section. We assume that all travelers are routed in the dynamic system optimal (DSO) situation where the network total travel time of all travelers is minimized. A DSO condition is more efficient than a Dynamic User Equilibrium (DUE) condition, though the latter could be regarded as the real-world situation, where travelers only focus on their own benefit rather than the benefit of the system. In DUE situation, all travelers between the same ODT pair will have the same travel time. To model the SO-DTAP, this study uses a simulation based DTA modeling approach with a path-based GP algorithm.

The reason why the path-based GP algorithm is chosen is twofold: 1) the GP path-based algorithm stores the utilized path set automatically as the algorithm is executed. 2) the GP path-based algorithm guarantees a convergence to the DSO condition. Moreover, per our experience, GP converges in relatively few iterations, meaning that path storage and computation time issues do not arise in our network.

In the following section, we will first introduce the DUE and DSO formulation. In this study, DUE could be regarded as a real-world case control group, as opposed to the proposed platform leading to the DSO situation. Secondly, we will introduce the traffic load-based link performance function, which guarantees a convex objective function and a positive-definite Hessian matrix for a quasi-newton update in the GP algorithm. The convex objective function guarantees that the local optimal is the global optimal, and the positive-definite Hessian matrix guarantees the validity of quasi-newton update. Thirdly, we will introduce the path-based GP algorithm to solve the SO-DTAP. Lastly, the convergence criteria will be introduced.

Dynamic User Equilibrium (DUE) and Dynamic System Optimal (DSO) Formulation

Rather than a DSO formulation, a DUE formulation is first introduced below. When the link travel time functions in the objective function are replaced link marginal cost functions, the DUE formulation becomes a DSO formulation, as is well known.

To further consider agent-level behavior, an agent-based DUE formulation is adopted in this study and presented in the section (the model is shown from Eq. (1) to Eq. (6)).

$$\min Z = \sum_{t \in T} \sum_{a \in A} \int_0^{x_{a,t}} t_{a,t}(w)\, dw \;\; \forall\, t \in T, a \in A \tag{1}$$

Subject to:

$$q_{\tau}^{rs} = \sum_{i \in I} \sum_{p \in P_{\tau}^{rs}} h_{i,\tau}^{rsp} \; \forall r, s \in R, \tau \in T^D \tag{2}$$

$$h_{i,\tau}^{rsp} = \begin{cases} 1 & if\ path\ p\ for\ OD\ pair\ r,s\ is\ used \\ 0 & otherwise \end{cases} \forall i \in I, \tau \in D \tag{3}$$

$$\sum_{p \in P_{\tau}^{rs}} h_{i,\tau}^{rsp} = 1 \forall i \in I \tag{4}$$

$$x_{a,t} = \sum_{i \in I} \sum_{r,s,\tau} \sum_{p \in P_{\tau}^{rs}} h_{i,\tau}^{rsp} \delta_{i\tau a,t}^{rsp} \; \forall r, s \in R, i \in I, p \in P_{\tau}^{rs}, \tau \in D \tag{5}$$

$$\delta_{i\tau a,t}^{rsp} = \Psi\left[h_{i,\tau}^{rsp}, \forall i, r, s, p, \tau\right] \forall r, s \in R, i \in I, p \in P_{\tau}^{rs}, \tau \in D, a \in A \tag{6}$$

In the objective function Eq. (1), $x_{a,t}$ is the traffic "load" of link a at time t, i.e., the number of vehicles presented in link a at time t. $t_{a,t}(\cdot)$ is the link travel time of link a at time t, with respect to a certain amount of traffic "load". The objective function sums all the links over the link set A, and sums all the timesteps t over the timestep set T.

Instead of considering traffic patterns in an aggregated level, Eq. (2-6) is formulated in an agent-based level. In Eq. (2), q_{τ}^{rs} represents the traffic flow (veh/h) between origin r and destination s at the departure time τ, where $h_{i,\tau}^{rsp}$ is an indicator variable. For agent i who departs at time t from origin r to destination s, if path p is used, then $h_{i,\tau}^{rsp} = 1$. Otherwise, $h_{i,\tau}^{rsp} = 0$, as Eq. (3) shows. P_{τ}^{rs} is the path set of agents who depart at at time t from origin r to destination s. R is the node set of the network. T^D is the departure time set of the simulation.

Eq. (4) represents that for a given origin-destination-departure pair, (r, s, τ), each agent chooses one path p from the path set P_{τ}^{rs}. Eq. (5) transfers the disaggregate agent path flow back to aggregate link flow. $\delta_{i\tau a,t}^{rsp}$ is the time-dependent individual link-path incidence matrix for each agent i, departing at time τ from origin r to destination s.

In Eq. (6), the term Ψ represents the calculation of enumerating traveled links of a path p for agent i, then transfer it to the time-dependent link-path incidence matrix $\delta_{i\tau a,t}^{rsp}$.

As mentioned above, the only difference between DUE and DSO formulation is their objective function, given the same constraints in Eq. (2)-Eq. (6). The agent-based DSO formulation adopted in this study is presented in Eq. (7).

$$\min Z = \sum_{t \in T} \sum_{a \in A} \int_0^{x_{a,t}} mc_{a,t}(w)\, dw = \sum_{t \in T} \sum_{a \in A} x_{a,t} t_{a,t}(x_{a,t}) \; \forall\, t \in T, a \in A \tag{7}$$

The objective function in Eq. (7) minimizes the agent-level total travel time for all links in set A and for all time steps in set T.

The agent-based extension brings a significant number of variables to the traffic assignment mathematical formulation. Furthermore, the temporal dynamics embedded in the DTA model increase its complexity. To solve this problem practically, the GP algorithm, a path-based algorithm which solve DTA problem efficiently by simply adjusting path flows between ODT pairs, is adopted in this study. However, before introducing the GP solution algorithm, we will first introduce the link performance function relating link travel time and the traffic "load" on it.

Traffic Load-based Link Performance Functions

In Eq. (1) above, the objective function is defined using the traffic load, $x_{a,t}$. The actual traffic load (i.e. number of vehicles on a certain link) assigned on any link in any discrete time step determines the link speed and travel time, with a monotonically increasing function. It results from the fundamental diagram which always has a non-increasing speed-density function. Thus, we can capture the congestion effects if density exceeds the critical density while keeping Eq. (1) convex. Note that this avoids a problem in using link flow as a variable, in that it causes the travel time function to "bend backwards" and cause high travel time at low flows too — a problem that is assumed to be negligible in the longer-period static assignments but cannot be neglected in the shorter period dynamic assignment.

Therefore, a modified Greenshields speed-density relationship is used for the load-based link performance function. The modified Greenshields speed-density relationship is shown below:

$$u_a^t = u_{min,a} + \left(u_{max,a} - u_{min,a}\left(1 - k_a^t / k_{j,a}\right)\right), \forall\, t \in T, a \in A \tag{8}$$

$$f_a^t(k_a^t) = \frac{L_a k_{j,a}}{u_{min,a} k_{j,a} + \left(u_{max,a} - u_{min,a}\right)\left(k_{j,a} - k_a^t\right)}, \forall a \in A \tag{9}$$

where $k_a^t \leq k_{j,a}$, density for a certain link a at time t is less than or equal to its jam density $k_{j,a}$. $u_{min,a}$ (ft/sec) is the minimum speed at the jam density for a certain link a. $u_{max,a}$ (ft/sec) is the free flow speed for a certain link a. k_a^t (veh/mile) is density for a certain link a at time t. $k_{j,a}$ (veh/mile) is the jam density for a certain link a at time t. L_a is the length of link a. $f_a^t(\cdot)$ is the travel time for a certain link a at time t. Thus $f_a^t(\cdot)$ is monotonically increasing with k_a^t, where $k_a^t = x_a^t / n_a L_a$, n_a is the number of lanes for link a.

The path-based gradient projection algorithm

In this study, we adopt the GP algorithm to solve simulation-based SO-DTAP in a mesoscopic model, with simulation time step fixed at 15 seconds.

Convergence Criteria

In this study, we adopt the Relative Root Mean Squared Error (R_RMSE) and the Relaxed Duality Gap (RDG) as our convergence criteria. The Root Mean Squared Error (RMSE) is calculated through the following formula:

$$RMSE = \sqrt{\frac{\sum_{\tau}\sum_{r}\sum_{i\in N}\left(\beta_{\tau,n}^{ri} - \beta_{\tau,n+1}^{ri}\right)^{2}}{\Gamma}} \tag{10}$$

where $\beta_{\tau,n}^{ri}$ is the nodal marginal cost time for agents departing from origin r to node i at time τ in iteration n. $i \in N$ represents that node i is in the set of all nodes N in the dynamic one-to-all shortest path finding algorithm. $\Gamma = R \times T \times (N-1)$, where R is the number of origins, and T is the number of departure timesteps, and N is the number of nodes in the network. Therefore, the R_RMSE could be calculated as:

$$R\_RMSE = \frac{RMSE}{\left(\frac{\sum_{\tau}\sum_{r}\sum_{i\in N}\beta_{\tau,n}^{ri}}{\Gamma}\right)} \tag{11}$$

Since we are interested in the SO-DTAP, we want to know whether the path-based System Optimal condition is satisfied. That is, all the utilized paths given a certain (r, s, τ) pair share the same marginal cost. The relaxed duality gap is to compare the marginal travel cost between non-shortest path and the shortest path in an aggregated way for all ODT pairs. Therefore, Relaxed Duality Gap (RDG) could be calculated through the formula below:

$$RDG = \frac{\sum_{\tau}\sum_{r}\sum_{s}\sum_{p\in P_{\tau}^{rs}} h_{\tau,n}^{rsp} \cdot max\left(0, d_{\tau,n}^{rsp} - d_{\tau,n}^{rs\bar{p}} \cdot (1+\omega)\right)}{\sum_{\tau}\sum_{r}\sum_{s} q_{\tau}^{rs} \cdot d_{\tau,n}^{rs\bar{p}}} \tag{12}$$

Where ω is the travel cost convergence. If ω is set to be zero, there is zero tolerance between the path marginal costs for shortest paths and non-shortest paths. In our simulation settings, ω is set to be zero.

For the control group, namely, the DUE condition, all the marginal costs are replaced the travel time costs.

Fair allocation of supply with pricing component

In this section, the second module of this smart mobility platform - the envy-minimization price matching module. The Theory of Zonal Pricing with Envy is introduced first, laying the foundation for envy-minimization calculations. Then the Dynamically Allocated System Efficiency with Envy

Minimization-Price Matching (DASEEM-PM) is introduced, which is implemented and analyzed in this study.

The Theory of Zonal Pricing with Envy

A major cause of congestion is the 'selfish' travel behavior of individual drivers. This travel behavior has been codified in the form of Wardrop's 1st principle (10) which states that drivers continue to minimize their travel time until it cannot be further improved—thus the travel times of all used routes are equal. This equilibrium condition is called User Equilibrium (UE), which is also known as Nash Equilibrium.

This selfish behavior aggravates traffic conditions even if additional infrastructure facilities in the form of new lanes are provided since travelers want to use the newly developed shortest route. To achieve the system optimal condition, demands should be well distributed over the available supply. Boyce and Xiong present graphical examples of how drivers are dispersed in a system optimal (SO) state (31). In the SO condition, dispersing vehicles on a network minimizes total travel time of the transportation system. The SO assignment inherently lacks desirable equity property because travel time differences among SO routes. Although the SO assignment improves the overall social welfare, the travel times among the routes in the SO pattern are different. This implies that some guided drivers experience unfairness (29).

For transportation system management, our main interest is in maximizing the efficiency of a system given the supply. On the other hand, from a social justice point of view, fair allocation of supply to demand is also a pivotal issue. Both terms conflict with each other; therefore, a solution satisfying both is unlikely to be achieved. For example, expected allocations for maximizing system efficiency indicate that the supply should be allocated unequally to different agents, but it is almost impossible to impinge upon the agents' freedom to select their travel option. Thus, a strategy for maximizing efficiency with various options is nonetheless poorly applied in an actual world because of unfair variances of alternatives. SO routing strategies in transportation assignment problems are examples. Generally, SO in moderate traffic is accompanied by unfair problems in that the quality of allocation is inequitable.

It is evident that an agent feels disgruntled if a system manager guides an agent to an allocation that is distinctively slower than that of others. The level of feeling of unfairness might be different according to the agent's valuation of an allocation. Thus, our approach considers the individual level of symmetric comparisons of agents' own yardsticks at the individual level. Recognizing the heterogeneity of individual travelers, we can minimize the system-wide envy level.

To design agent-level transportation systems, we propose to use the concept of "Envy", which is a theory from Economics, as a new paradigm for fairness, efficiency, and behavior. With the possible technology of peer-to-peer data exchange, it is not difficult to imagine how individuals behave regarding their transportation options or how a system manager designs transportation systems. When an agent can access other agents' route information, an agent might make their best effort to minimize the equality gap with others'. A system service manager could become concerned with this user's behavior. On the other hand, a system manager might prefer to design a system maximizing efficiency or profit. The best strategy is to design a system that achieves optimum efficiency while not intruding on users' freedom of selection.

In the 1940s, Envy was initially employed for a fair division problem by economists and mathematicians (32). Gamow and Stern introduce the Envy-Free (EF) theory in the context of the fair cake-cutting problem (33) . Envy-Free implies that each agent believes that their allocation is greater than or at least the same as the share of others; each player, in turn, is satisfied with an allocated piece of cake according to their preference. Thus, an EF region exists if there is a certain level of heterogeneity of preference. Varian uses Envy to design a fair allocation system (34) . He defines fair allocation in terms of Equity, Envy, and Efficiency. Here are the definitions and its relationships.

As we discussed, our research interest is to find the optimum (Efficient) allocation of transportation supply while agents believe their allocation is equitable; this interest is in line with Varian's definition of Fairness.

To implement Envy theory in the transportation domain, we define agents' behavior as follows:

Definition 1. Each agent has his/her own preference θ_i to travel options (e.g., value of time) and these preferences are heterogeneous.

Definition 2. The distribution of valuation is known to a system manager and the distribution is not necessarily based on certain well-known distributions, such as a normal distribution. However, the output of the valuation function is always non-negative according to the positive allocations.

Definition 3. An agent compares his/her travel option with others' only who are in the same travel property (i.e., origin and destination).

Definition 4. An agent ($i \in i^{rs}$) feels envy when he/she finds that an option given to or selected by other travelers ($j \in i^{rs}$) provides a higher value than his/her current selection (Eq 12).

$$e_{ij} = \left(V_{ij}(\theta_i, t_j) - V_{ii}(\theta_i, t_i)\right)\delta_{ij} \tag{13}$$
$$\forall\, i, j; i \neq j; i, j \in i^{rs}$$

where δ_{ij} is 1 if "Envy" is positive and zero otherwise.

This definition ensures privacy for travelers because a system is not necessary to expose other vehicles' personal information (e.g., value of time). This implies that an agent is indifferent to other agents' preferences. In other words, it does not matter for an agent to identify how rich other agents are, what their trip purposes are, or how urgent they are. An agent evaluates its envy based on its interpretation. An agent judges its envy by comparing others' options using their own criteria (Definition 1). In this study, the value of time is used, but it can be extended to various normalizers such as the value of emotion. We can interpret Eq. (13) that an agent does not feel envy when its valuation is higher than that of others; thus, envy of i to j (e_{ij}) is always non-negative.

Definition 5. Agent's greedy behavior to the shortest path

In addition to mutual envy comparisons among agents, an agent feels envious (e_{is}) if its allocation is worse than that of the shortest path. This definition is equivalent to the basic assumption of UE. Like Definition 1 and Definition 4, envy is evaluated based on an agent's valuation. Interestingly, this definition is in line with the objective function for a solution of a gradient descent projection for assignment models that is used for a path-based traffic assignment algorithm (16). This finds an equilibrium solution by comparing a route with the shortest path and adjusting traffic loads to the path.

$$e_{is} = \big(V_{is}(\theta_i, t_s) - V_{ii}(\theta_i, t_i)\big)\delta_{is} \tag{14}$$
$$\forall i, j;\ i \neq j$$

where δ_{ij} is 1 if "Envy" is positive and zero otherwise

Definition 6. Agents change their travel option until they do not feel envious of others' (Envy minimizer).

This is based on a different behavioral assumption than employed in traditional static or dynamic traffic assignment models. Static traffic models postulate that day-to-day travel experiences make agents have full information about traffic after certain periods that affect route choice decisions, that converge at a certain equilibrated level. This assumption is valid for the situation where agents rely on such static traffic information as paper maps, and even digital maps without real-time traffic information. With the availability of real-time traffic information (mobile applications, radio, digital maps, and Variable Message Signs) dynamic traffic assignments imply User Optimum behavior assumption, i.e., that a traveler makes a route decision based on current traffic conditions. Our future vision is drawn on Connected Autonomous Vehicles (CAVs) and block-chain technology to facilitate the possibility of peer-to-peer travel information exchanges, which enable travelers to compare their options with that of others. In turn, an agent changes a travel option until it feels comfortable with the other agents' allocation.

The optimization of social welfare for maximizing efficiency and minimizing envy is our research interest; for the feasible optimization problem, we relax the definition of envy (3.1) to Eq. (15), and Eq. (16).

$$e_{ij} \leq My_{ij} \; \forall \; i,j; \; i \neq j \tag{15}$$

$$-e_{ij} + [V_{ij}(\theta_i, t_j) - V_{ii}(\theta_i, t_i)] \leq M(1 - y_{ij}) \; \forall \; i,j; \; i \neq j \tag{16}$$

Where M is a large number, and $y_{ij} = 0{,}1; e_{ij} \geq 0$.

If $y_{ij} = 0$, then $e_{ij} \leq 0, -e_{ij} + [V_{ij}(\theta_i, t_j) - V_{ii}(\theta_i, t_i)] \leq M$.

If $y_{ij} = 1$, then $e_{ij} \leq M, [V_{ij}(\theta_i, t_j) - V_{ii}(\theta_i, t_i)] \leq e_{ij}$.

When we consider valuation as a multiplicative function of both a value of time (θ_i) and travel time (t_i), Eq. (15) is simplified as Eq. (17) and Eq. (18). These equations deal with each agent's heterogeneity (i.e., valuation of time, θ_i) and it is worthy to note again that envy is evaluated differently by point of view. As shown in Eq. (18), other agents' value of time or their level of envy does not matter to an agent i.

$$-\theta_i \mu_i + e_{ij} \; \geq \; -\theta_i \mu_j \tag{17}$$

$$e_{ij} \geq -\theta_i (t_j - t_i) \tag{18}$$

Dynamically Allocated System Efficiency with Envy Minimization-Price Matching (DASEEM-PM)

Dynamically Allocated System Efficiency with Envy Minimization-Price Matching (ASEEM) is applied in this project. Its objective function consists of the objectives of efficiency and equity; as in Eq. (19). Here, efficiency is considered as minimizing the total travel time of the entire system. We consider equity by minimizing the sum of envy of an agent. Here, the equity term might be overweight according to the number of agents if we sum all the envy values of an agent's comparisons. This overweight problem can be tackled by the setting of β coefficient. However, we reduce redundancy of the envy term by only calculating maximum envy of agents among envy sets from individually symmetrical comparisons, we can reduce redundancy of the envy term. This is consistent with the Minimax approaches for envy optimizations. Here, α, β are weight parameters. When $\alpha = 0$, the goal of optimization becomes standard minimax envy-minimizing optimization. On the other hand, $\beta = 0$ brings the results of the SO assignment problem.

$$Min\ obj = \alpha \sum_{t \in T} \sum_{a \in A} x_{a,t} t_{a,t}\left(x_{a,t}\right) + \beta \sum_{i \in I} \max_{i \neq j}\{e_{ij}\} \tag{19}$$

Below are the constraints for this problem. Note that this problem is a mixed integer linear programming, which is computationally complex.

The optimization is subject to:

$$q_\tau^{rs} = \sum_{i \in I} \sum_{k \in K_\tau^{rs}} h_{i.\tau}^{rsk} \quad \forall\, r, s \in R; \tau \in T^D \tag{20}$$

$$h_{i,\tau}^{rsk} = \begin{cases} 0 & if\ path\ k\ is\ used \\ 1 & otherwise \end{cases} \qquad \forall i, \tau \tag{21}$$

$$\sum_i h_{i,\tau}^{rsk} = 1 \qquad \forall i, k \tag{22}$$

$$x_{t,a} = \sum_{i \in I} \sum_{r,s,k,\tau} h_\tau^{rsk} \delta_{it\tau a}^{rsk} \qquad \forall r, s \in R, i \in I, k \in K^{rs} \tag{23}$$

$$\delta_{it\tau a}^{rsk} = \Psi\left[h_{i,\tau}^{rsk}, \forall i, r, s, k, \tau\right] \quad \forall\, r, s, q \in q^{rs}, k \in K_\tau^{rs}; a \in A \tag{24}$$

$$\sum_{r,s,k,\tau} -t_a \delta_{it\tau a}^{rsk} \theta_i + e_{ij} - p_{i\tau}^{rs} \geq \sum_{r,s,k',\tau} -t_a \delta_{jt\tau a}^{rsk'} \theta_i - p_{j\tau}^{rs} \qquad \forall i, j \in I\ \ i \neq j \tag{25}$$

$$\sum_{i \in I} p_i^{rs\tau} = B^{rs\tau} \qquad \forall\, r\,, s\,, \tau \tag{26}$$

$$0 \leq e_{ij} \leq e_{max} \qquad \forall i, j; i \neq\ j \tag{27}$$

Here, $x_{a,t}$ and $t_{a,t}(x_{a,t})$ are the traffic load of link a at time t and its travel time respectively, both of which are aggregated-values of the individual's path-link incidence matrix. This implies that the first objective function is of importance for systemwide travel time minimization problem. The second objective function consists of envy comparisons at an individual level. In other words, our objective has two components: 1) total travel time and 2) minimization of the sum of the maximum envy of individual, which allow us to solve two objectives in two steps. If we define e_{ij} as a very small value near zero, the optimization results in either User Equilibrium or All or Nothing assignment. With the proper value of α, β, and γ we can generalize the state of UE as Lemma 1.

Eq. (20) to Eq. (27) are model constrains that reformulated from an aggregated traffic assignment model to incorporate a version of dynamic traffic assignment model at the agent level. Instead of regarding flow as aggregated behavior, these constraints are formulated to consider each agent. For example, Eq. (20) is formulated for OD demand conservation which is the sum of an agent's path flow binary $h_{i,\tau}^{rsk}$. The value of $h_{i,\tau}^{rsk}$ is 1 if path k for rs is used for agent i departing at time τ as in Eq. (21). Consequently, the sum of $h_{i,\tau}^{rsk}$ for agent i is a unit value, as in Eq (22). The term $\delta_{it\tau a}^{rsk}$ is a path-link variable of an individual i whose origin and destination are r and s, respectively, the path is k, departure time is τ, and time to arrive a link a at time t, Eq. (24). The term Ψ represents the calculation for enumerating traveled links of a path k for agent i, then converting it to the path-to-path link incidence matrix ($\delta_{it\tau a}^{rsk}$) Link flow at time t, $x_{a,t}$, is the sum of agents passing link a at time t, which is represented in Eq. (23).

Peer to Peer envy comparison constraints is formulated as from Eq. (*25)* to Eq. (*27).* Eq. (25) addresses envy comparison. It indicates that if agent i pays more than agent j ($p_i \geq p_j$) for the same path travel time, agent i feel envious (e_{ij}) at the amount of the price difference. Similarly, if the path travel time of agent j is shorter than that of agent i without a price difference ($p_i = p_j$), agent i feels envious (e_{ij}) to agent j. It is noteworthy that the feeling of envy is only measured by agent i's valuation θi In Eq. (25), $\sum_{r,s,k,\tau} -t_a \delta_{it\tau a}^{rsk} \theta_i$ is the path travel time of path k for agent i. Thus, envy in the latter case, can be interpreted as a degree of travel time difference as perceived only by agent i.

In this project, the zonal pricing is generated following a model related to envy, not the simple user equilibrium.

Simulation input and settings

This report proposes a smart mobility platform with fair congestion pricing and efficiently distributed incentives. The effectiveness of the proposed platform is evaluated in an urban network which is larger than Nam's work (5). The proposed platform is applied at East-Los Angeles rectangular Network (around $10mi \times 4mi$) along a section of Interstate 10 (I-10) highway. We conduct the simulation under the situations of the dynamic user equilibrium-DUE (as control group); dynamic system optimal-DSO without envy-minimization price matching (to evaluate the envy without fair congestion pricing); as well as the DSO with envy minimization price matching (as the test group). Firstly, we describe the input data of the simulation and then the simulation settings in this section.

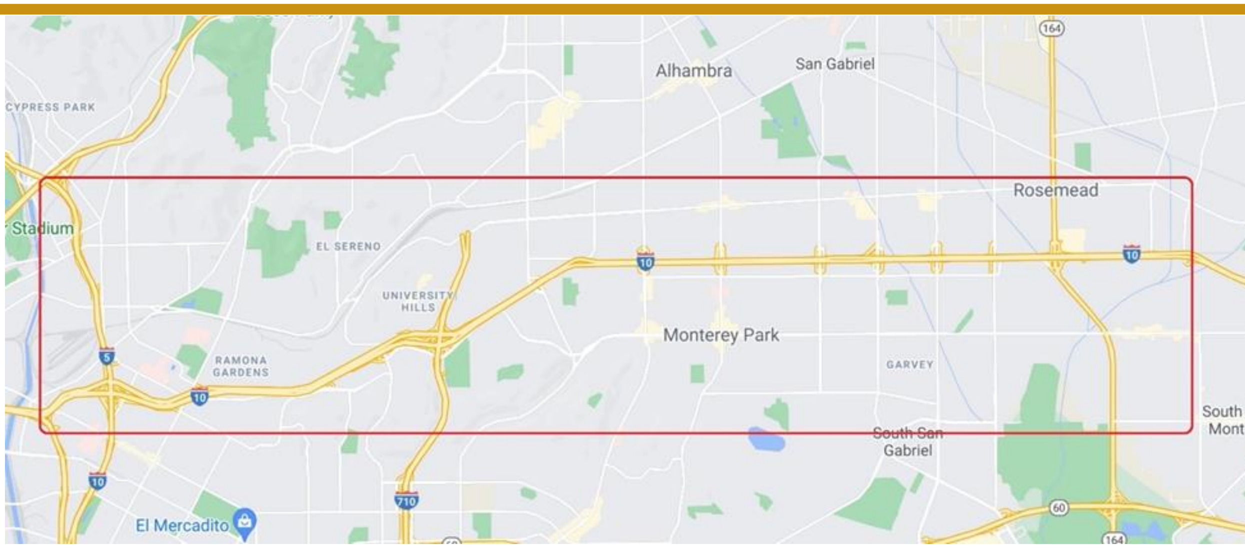
Data Description

The input data includes three parts - the supply part, the demand part, and the agent attributes. The supply part mainly consists of transportation network information like links and nodes and their properties. The demand part consists of the one-hour average morning peak period OD table., The agent attributes part consists of the VOT information of all agents.

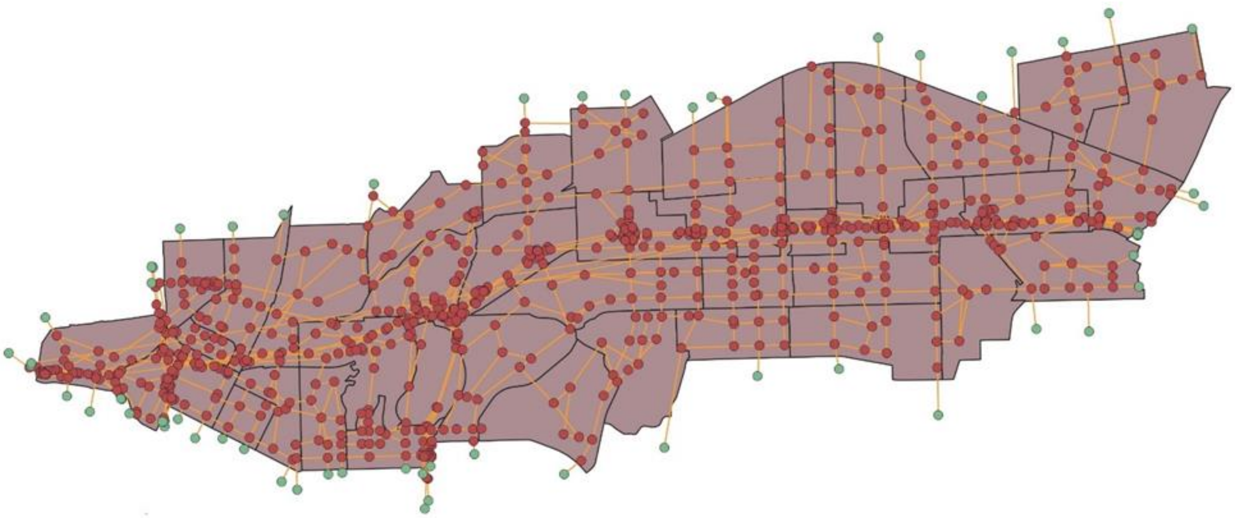
Supply data: the East Los Angeles I-10 Network

LA I-10 network is a large-scale realistic network consisting of 799 nodes and 1927 links, as illustrated in Figure 1 (a) and (b) below. The network is cut from the network of LA county in the California Statewide Travel Demand Model (CSTDM) (Figure 1 (b)). Among all 799 nodes, 60 of them are external nodes, which connect the selected network to the traffic from outside and 38 of them are Traffic Analysis Zone (TAZ) centroids, from which we assume the zonal traffic comes. The I-10 freeway section we analyzed in this report is a 10.5-mile corridor starting from El Monte to Downtown LA. There are three major highways passing through the I-10 network, which are - I-10 freeway, I-5 freeway, and I-710 freeway

Figure 1. Illustration of LA I-10 network: (a) From Google Maps; (b) From QGIS



(a)



(b)

The excerpts of node and link data are shown in *Table 1* and *Table 2*, respectively. Each of the excerpts includes the first five pieces. Each node includes the ID with its coordination ($x - y$); and each link includes attributes of from node, to node, length, jam density, free flow speed and number of lanes.

Table 1. The excerpts from the node data (the first five pieces)

Node_ID	X	Y
4032	163658.7	-438183
4080	164851.9	-438574
4100	165855.3	-437220
4101	165013	-437059
4102	166827	-437275

Table 2. The excerpts from the link data (the first five pieces)

Link_ID	from	to	length(ft)	k_j(veh/mile)	free_speed(ft/sec)	noflane
0	4032	43492	2341.627	160	22.00001	9
1	4032	43493	887.7264	160	22.00001	9
2	4032	142056	1756.075	160	22.00001	9
3	4080	43497	2528.962	160	22.00001	9
4	4080	43498	728.8512	160	22.00001	9

Demand Input: Trip Table

We derive the demand input trip table from California Statewide Travel Demand Model (CSTDM).The demand table is obtained according to the following steps: we used the 4-hour morning peak OD trip table from California Statewide Travel Demand Model (CSTDM) and performed a sub-area analysis to get the OD trip table for the LA I-10 network area. The resulting trip table from sub-area analysis is a 98×98 OD table, where each row and column include 38 TAZ centroids and 60 external nodes. We then divide the trip table by 4, converting the 4-hour morning peak trip table into an average hourly morning peak trip table with 6,148 non-zero OD pairs and 78,196 trips.

Table 3. The excerpts from the trip data (the first five pieces)

Id	Origin	Destination	Type	Vol
1	4032	4080	Veh	4.224542
2	4032	4100	Veh	3.0892
3	4032	4101	Veh	2.39438
4	4032	4102	Veh	1.529834
5	4032	4103	Veh	0.669927

Agent attribute input: individual VOT

The envy minimization price matching in our model is implemented based on a peer-to-peer path-travel time comparison. Agents evaluate the difference between their path travel times using their own yardsticks. To calculate one agent's envy towards other agents, we need to know two components: (1) the path travel time difference between them; (2) the value of time of that agent. We will then introduce how the value-of-time (VOT) of the agent is generated in the subsequent paragraphs.

In the envy minimization process, the decision variables are the price paid by or given to each agent– (between p_i and p_j). The input parameters are values of time θ_i of agents from the activity system, and agents' path-level travel time, t_i and t_j, from the transportation system obtained from the dynamic traffic assignment model. In this study, we assume VOTs for individuals within each zone are generated from a log-normal distribution, with a mean and standard deviation. The reason why we assume VOT has a log-normal distribution assumption is that log-normal distribution never begets negative values. This assumption aligns with the distribution of individual VOT, as there are no negative VOTs for agents.

Value of time is usually assumed to be a percentage of household average hourly wage. In Bento et. al.'s work (6), to calculate household average hourly wage, they assume each household has two people and each person works 2040 hours annually. In their paper, the results showed that in the LA I-10 area, individual VOT is about 60% of their average hourly wage. In this report, we obtained the mean and standard deviation of VOT from Bento et. al.'s work to generate individual VOT from the log-normal distribution (6). In this report, we also adopted their logic of calculating average hourly. Thus, the zonal average value of time is calculated as equation (25):

$$\theta_i = 0.6 \times \frac{HH\_inc}{2 \times 2040} \tag{2}$$

Where HH_inc is the zonal average annual household income. We obtained the average zonal household income from the United States Census Bureau data of 2013[2], so that our settings align with the research settings in Bento et. al. They also used the I-10 express lane usage data to calibrate people's VOT in the year of 2013. In Bento et. al.'s work (6), they estimated the mean of VOT ($7.16/h) is close to the standard deviation ($7.84/h) of it. So, in our input setting, we assume zonal VOT has the same mean and standard deviation.

The zonal input VOT are shown in the Table 4:

Table 4. The excerpts of VOT and in zonal data (the first five pieces)

TAZ	Vot_mean (dollar/h)	Vot_σ (dollar/h)
4032	7.287941	7.287941
4100	7.016176	7.016176
4101	7.016176	7.016176
4102	8.496912	8.496912
4919	8.496912	8.496912

For agents coming from the 38 TAZ centroids, the VOT of each agent is derived from the lognormal distribution with its zonal mean and zonal standard deviation shown in Table 4. For trips coming from the 60 external nodes, the VOT of each trip is derived from the lognormal distribution with mean 7.16 and standard deviation 7.84. Here we use the exact number obtained from Bento et. al.'s work (6).

Dynamic Traffic Assignment (DTA) module settings

As described in the methodology section, the model includes a DTA module and an envy-minimization price-matching module. We will describe the settings of DTA module here.

Simulation timesteps

We now describe the settings in the DTA simulation module. For the mesoscopic dynamic traffic assignment module, the simulation timestep is set to 15 sec. The demand input is a 1-hour average morning peak demand. However, due to congestion, the total simulation time for DUE and DSO might be different and longer than 1 hour.

[2] https://data.census.gov/cedsci/map?q=mean%20income%202013&g=0400000US06%248600000&tid=ACSST5Y2013.S1902&cid=S1902_C01_001E&vintage=2013&layer=VT_2013_860_00_PY_D1&mode=thematic&loc=34.0664,-118.0413,z11.1966

Speed-density relationship

As described in the methodology section, a modified Greenshields speed-density relationship is used to calculate the dynamic link travel times for all links at all timesteps based on the number of vehicles on them. The first derivatives and second derivatives of the Greenshields speed-density relationship are calculated using python package "scipy.misc[3]".

Number of iterations and convergence criteria

To solve the DTA problem, we use path-based gradient projection algorithms. We set the maximum number of iterations to 50, while the algorithm stepsize is set to 1 both in the DUE case and in the DSO case.

From the methodology section, we mentioned that we use two criteria to determine whether the algorithm is converged – Relative Root Mean Squared Error (R_RMSE) and Relaxed Duality Gap (RDG). The R_RMSE is set to 0.01 and relative_dual_gap is set to 0.5 in our experiment settings.

Agent number rounding

The proposed model is an agent-based DTA model. However, the DTA results from the gradient projection algorithm are flow-based, which don't have integer path flow. To do the agent-based envy comparison, we need to round the path flows to integers in a probabilistic way. For example, if we see a number like 11.4, we keep the integer part (11) but generate a random number with respect to the decimal part (0.4) to determine whether the agent number needs to add one (i.e. becomes 12). Thus, the flow-based DTA solution could be converted to agent-based DTA solution.

Envy-minimization price-matching module

The envy-minimization price-matching module receives the path travel times calculated from the DTA module and the individual VOT generated for agents from each zone. The envy-minimization problem is solved through gurobi optimizer. We set the lower bound for envy to be zero and the upper bound to be 10,000. We also set the lower bound of the calculated price to be $-10,000, while the upper bound of it to be $10,000.

[3] https://docs.scipy.org/doc/scipy/reference/misc.html

Result and Analysis

Network level transportation results

As mentioned in the "Agent number rounding" section, the model firstly conducts the flow-based results in a path-level, and they are converted into an agent-based results. Some parameters for algorithm performance evaluation, such as Vehicle Miles Traveled (VMT), Vehicle Hour Traveled (VHT), and the space-mean speed in the network would change after the agent number rounding.

VMT, VHT, and Space mean speed

Table 5 illustrates network level results as a whole, including network level VMT, VHT and space mean speed. As shown in Table 5, in the simulation settings, input trips are 78,196. In the agent-level, compared with the DUE solution, the VMT in our model (DASEEM-PM) is increased by 7%, while the VHT decreases by 5%, resulting in a 13% increase of network space mean speed from 31.24 mph to 35.32 mph. The flow-based solution is illustrated for readers' reference, although we mainly focus on the agent-based solution, because the agent-level envy comparison and envy-minimization should be executed at the agent-level.

Table 5. Comparison between DUE and DASEEM-PM

Method	VMT_ agent (mi)	VHT_ agent (h)	sms_ agent (mph)	VMT_ flow (mi)	VHT_ flow (h)	sms_ flow (mph)	Input_trips
DUE	1.51E+09	4.82E+07	31.24	1.39E+09	4.83E+07	28.85	78,196
DASEEM-PM	1.62E+09	4.58E+07	35.32	1.48E+09	4.69E+07	31.60	78,196

Results in time-dependent network

In this section, we show the network level time-dependent demand, cumulated departure/arrival curve, VMT, VHT and space mean speed curve respectively.

The network demand input is as *Figure 2* illustrates. For the first 6 minutes, 186 agents come into the network every timestep (15 seconds). Then, from the 6-12th minute, 557 agents come into the network every timestep. For the 12-18th minute, 743 agents come into the network every timestep. The number of agents entering the network decreases to 557 during the 18-24th minute, and then to 278 during the 24-36th minute and stays at 186 after the 36th minute.

Figure 2 Time-dependent demand curve

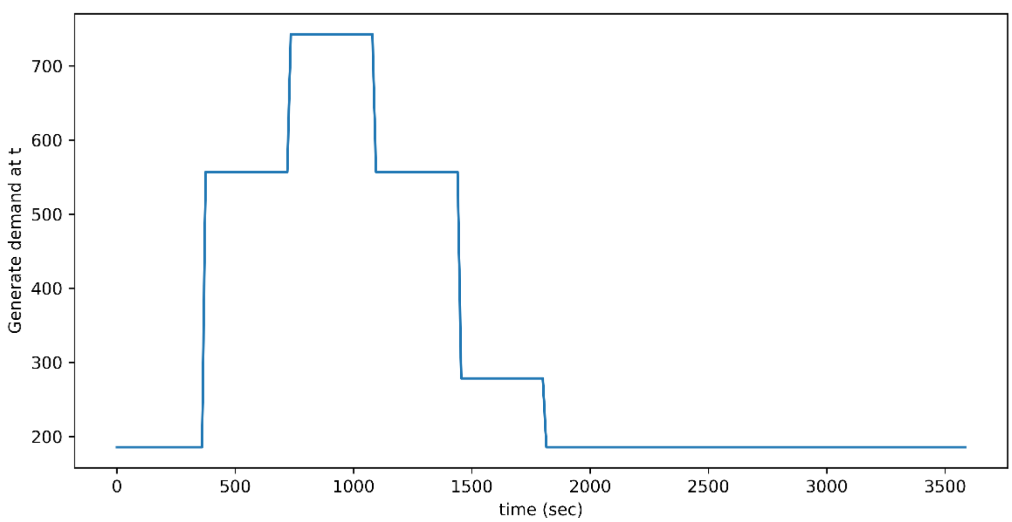


Figure 3 shows the time dependent departure and arrival curve. Only one hour of demand is loaded into the network. For the DUE case, the simulation ends at 1 hour 30 min (360 timesteps), while for the DSO case, the simulation ends at 1 hour 19.75min (319 timesteps). As both DUE and

DSO share the same dynamic demand profile, the departure curve for DUE case (departed DUE) would overlap the departure curve for DSO case (departed DSO).

As shown in Figure 3, from 0s to 600s, the arrival curves of DUE and DSO overlap. From about 600th sec to 2600th sec, DSO arrival curve is above the DUE arrival curve, which means less vehicles queuing (i.e. the difference between departure curve and arrival curve) in the network in DSO. As agents are assigned in the way that the total agent travel time is minimized Eq.(18), the network is less congested in DSO. From 2600th sec to 3700th sec, fewer vehicles enter the network and the number of vehicles queuing in the network becomes decreasing (i.e. the gap between departure curve and arrival curve decreases). During this period, the DSO arrival curve is under its DUE counterpart, which means more vehicles are queuing in the network, as some agents would travel through a longer path to make the system optimal. Therefore, during this period, the agent's arrival rate for DSO is lower than DUE's arrival rate. After the 3700th sec, DSO and DUE share a similar arrival rate. Finally, all agents arrive at their destinations at the 4800th sec in DSO, and at 5400th in DUE.

Figure 3. Time-dependent cumulated departure and arrival curve

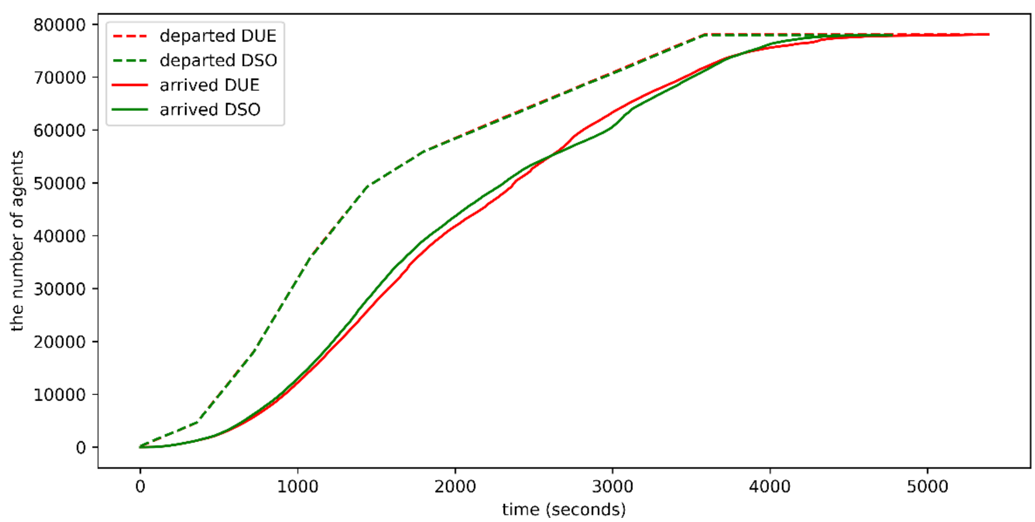


Figure 4 shows the time-dependent VMT curve in DSO and DUE. In general, the DSO curve(the green curve) is higher than the DUE curve (the red curve), as DSO makes some agents take longer distanced routes to maximize the system efficiency. Under DUE, agents choose the best (shortest) route, although their choices might lead to a more congested traffic condition. Figure 5 shows the time-dependent VHT curve in both DSO and DUE. In general, the DSO curve is below the DUE curve, because VHT is minimized in the case of DSO.

Figure 4. Time-dependent VMT curve

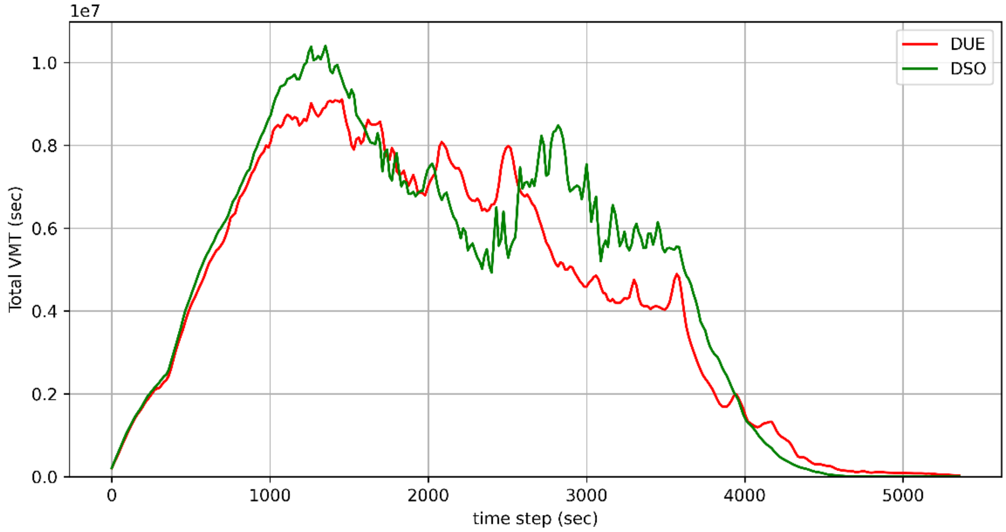


Figure 5. Time-dependent VHT curve

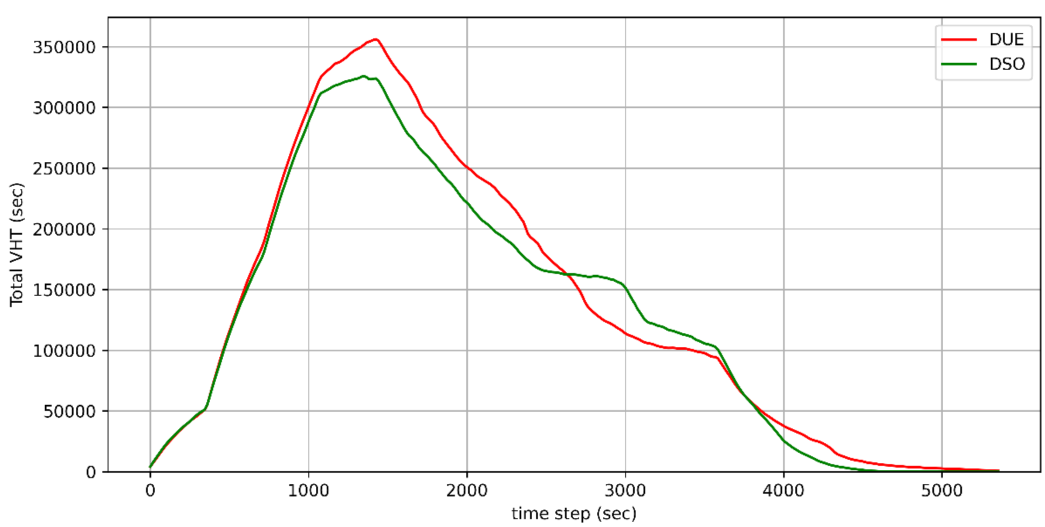
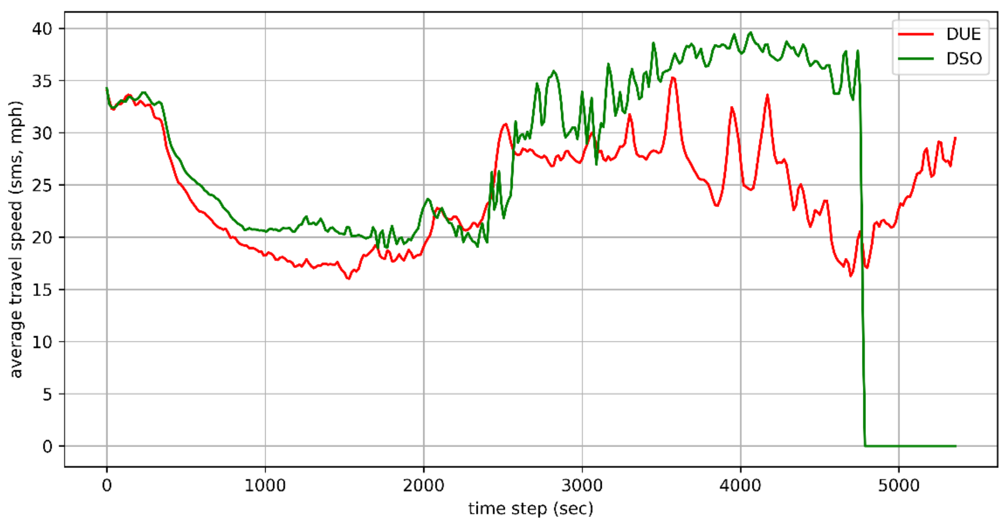


Figure 6 shows the space mean speed curve for the whole network under DSO and DUE. The space mean speed result aligns with the VMT and VHT results shown in Figure 4 and Figure 5. As Figure 6 shows, the DSO curve (green curve) is above the DUE curve (red curve), which means that the DSO has less congested network that the DUE. The space mean speed of DSO becomes 0 after 4800 sec as all trips arrive their destinations, and no vehicles are in the network.

Figure 6. Time-dependent space mean speed



In summary, as the network level results illustrate from Figure 3 to Figure 6, the DSO condition in DASEEM-PM could lead to a less congested condition than the DUE condition (regarded as the real-world condition).

Network level price matching results

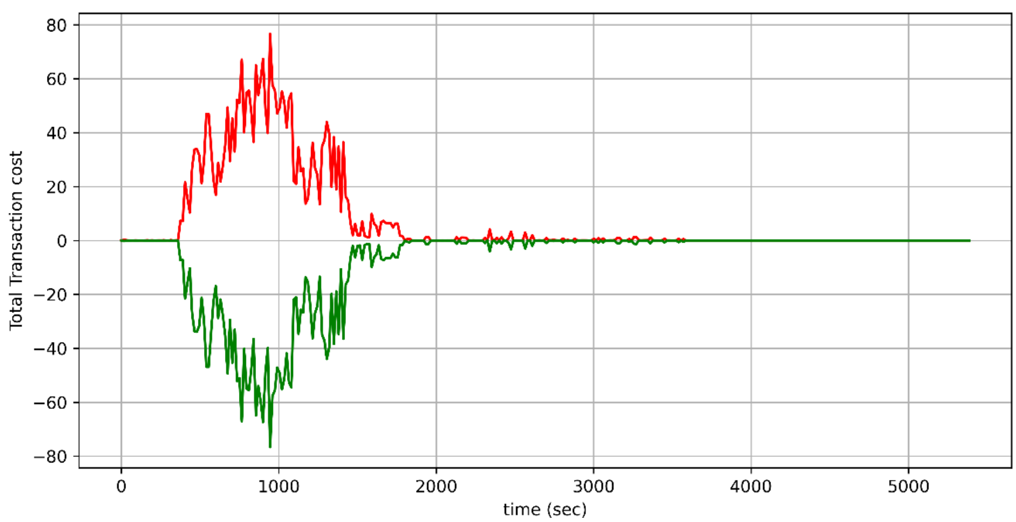
Under the price matching scheme, agents, from the same Origin-Destination-departure Time (ODT) pair, who travel on the shortest route shall make a payment to those who travel on the longer routes, with the objective of eliminating the envy created by travel time difference. We define tolls as monetary payments made by agents, and incentives as monetary receipts from agents.

Figure 7 shows the evolution of tolls and incentives in the network. From the first 6 minutes, as the demand is low, there are very few multiple paths, which means that only one route is found for each ODT pair. As a result, no envy is generated when agents travel only on one path, and no transaction is needed to eliminate the envy. After the 6th minute, as more agents enter the network, the network becomes more congested, and more paths are found for each ODT pair.

Once there are multiple paths for ODT pairs, the price matching scheme would calculate the optimal tolls and incentives to minimize the envy generated by different route travel times.

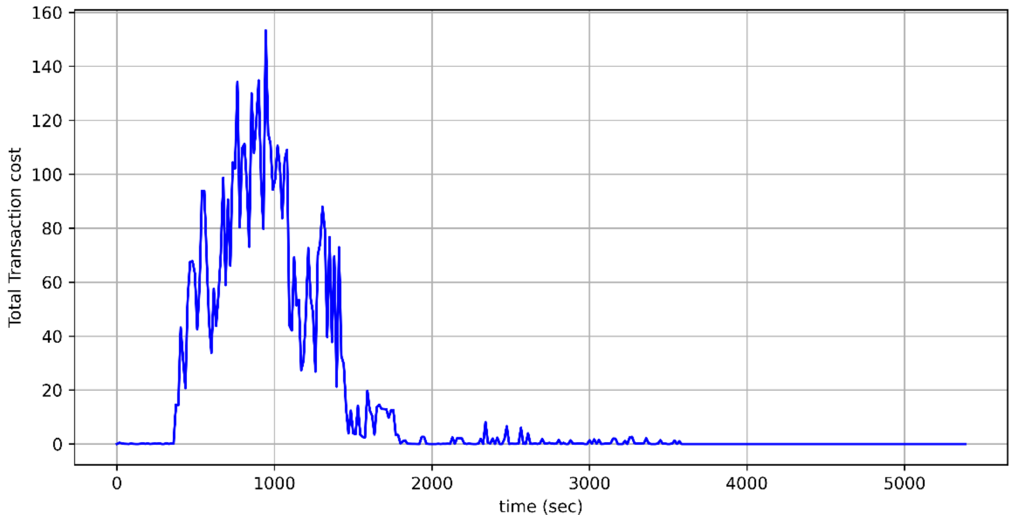
According to Figure 7, the highest price-match throughout the network is $76.6 at 945th second. Throughout the simulation period, the total tolls and total incentives are $2741.1, and the total transaction is $5482.2.

Figure 7. Time-dependent tolls and incentives



As in Figure 7 and Figure 8, most of the price matching happen from the 6th minutes to the 30th minutes. During that time, the network becomes relatively congested, and agents would feel envy due to the different path travel times in a large network. Since agents feel envy, they will use the price matching platform to negotiate their routes and pay each other. The price matching scheme is a good tool to reach a more efficient transportation system when it is congested, and multiple routes are found.

Figure 8. Time-dependent total transaction



Equity metrics analysis

In this section, we analyze the equity metrics, including envy, extra benefits, the payments that agents make, and the money that other agents receive from price matching.

Network level equity metrics analysis

The proposed platform, DASEEM-PM, could reduce the system inequity in the network level. DASEEM-PM could make the system reach DSO condition with a price matching mechanism. In this section, we compare the network level equity metrics (e.g., the envy and extra benefits) for DUE conditions and our proposed model (DASEEM-PM).

As illustrated in Table 6, all the equity metrics are defined in dollar terms. The matched prices are calculated based on comparing the different path groups' envy levels. One agent will be selected as a path group representative, and the path group pricing is calculated based on the comparison of the representative. So for each ODT pair, agents traveling on the same path share the same matched price. The matched price is either positive (making a payment) or negative (receiving a payment). For those who travel through longer routes, the maximum envy is perceived by the agent with the largest VOT. The Sum of Maximum Envy in Table 6 is the summation of the maximum envy for all the groups. For those who travel on the shortest routes, instead of feeling envy, they perceive extra benefits compared with the others in travel time. The minimum extra benefit is perceived by the one with the smallest VOT in the shortest path. The sum of minimum extra benefit in Table 6 is the summation of minimum extra benefit. It is worth noticing that the model is allocation efficient, which means that agents with higher VOT would be rerouted to a shorter path, while agents with lower VOT will be routed to a longer path.

Table 6. Equity metrics comparison between DUE and DASEEM-PM

Method	Sum of Maximum Envy (usd)	Sum of Maximum Envy without Price (usd)	Sum of Minimum Extra Benefit (usd)	Sum of Minimum Extra Benefit without Price (usd)
DUE	325.30	325.30	857.54	857.54
DASEEM-PM (DSO)	1.31E-07	3800.51	3227.13	7057.40

In DUE theoretically, all utilized paths share the same travel time for each ODT pair, while in practice, all utilized paths cannot share the same path travel time, due to the flow-based to agent-based rounding. Even if the travel times between paths are the same in the DTA flow-based result, the path costs will be different when flow-based results are converted to agent-based results. Given that there are some differences in the utilized path travel times in DUE, The Sum of Maximum Envy without price for DUE is $325.30, which is greater than zero, as Table 6 shows. In the DASEEM-PM case, the Sum of Maximum Envy without price is $3800.51, which is larger than that in DUE. As agents are routed to the longer paths, a larger amount of envy is generated in the system.

Due to the price matching mechanism, the Sum of Maximum Envy reduces from $3800.51 to $1.31E-07, when it comes from DUE to USO. Namely, it reaches the envy-free status for agents in the network. In the DUE, as there is no price matching, the Sum of Maximum Envy doesn't change, remaining at $325.30.

In DUE, the Sum of Minimum Extra Benefit without pricing is $857.54, which is larger than Sum of Maximum Envy without pricing ($325.30). It is because of the allocation efficiency condition where agents with higher VOT are routed to the shortest path, while ones with lower VOT are routed to the longer path. Under allocation efficiency condition, the smallest VOT in the shortest path group is still larger than the largest VOT in the non-shortest path group. Therefore, Sum of Minimum Extra Benefit without pricing is larger than the than Sum of Maximum Envy without pricing in both DUE and DASEEM-PM case. The Sum of Minimum Extra Benefit for DSO is larger than that in DUE, because of the travel time difference.

With price matching, the Sum of Minimum Extra Benefit in DSO reduces from $7057.40 to $3227.13. The payment made by agents on the shortest path decreases their extra benefit (i.e, the negative of envy). In DUE, Sum of Minimum Extra Benefit remains at $857.54.

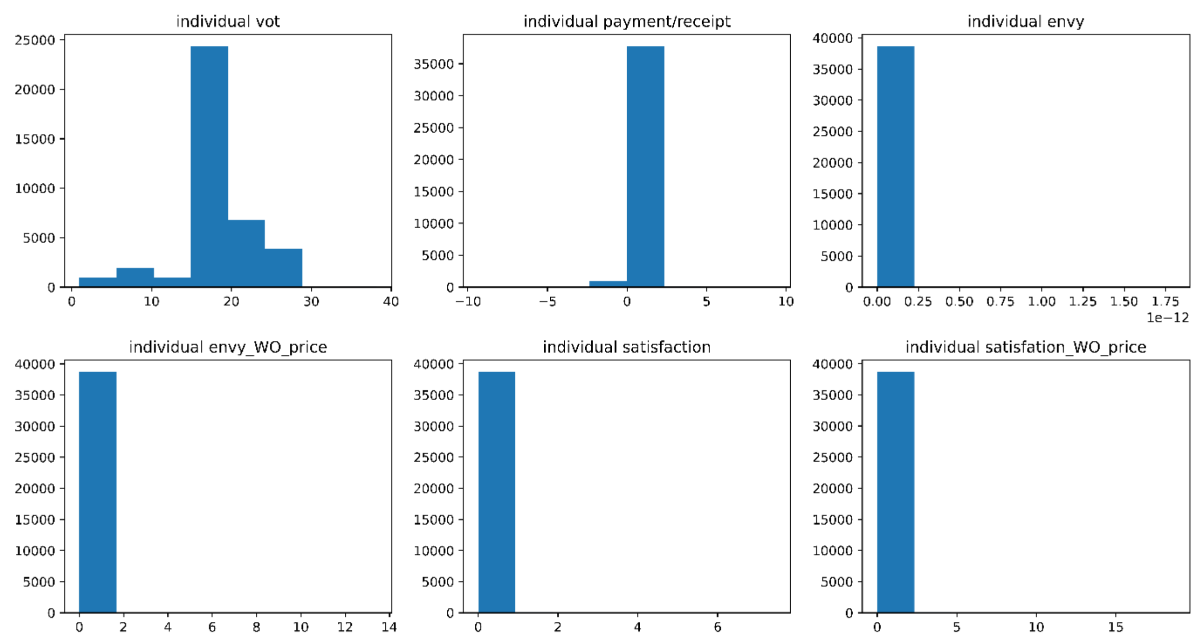
In summary, although the DASEEM-PM decreases Sum of Minimum Extra Benefit, it reduces the Sum of Maximum Envy to zero. The agents in the network reach the envy-free condition.

Agent level equity metrics analysis

20 minutes to 60 minutes during the simulation time period is selected for equity analysis at agent-level, which excludes the first 20 minutes warm-up period, and the clearing period after 60 minutes.

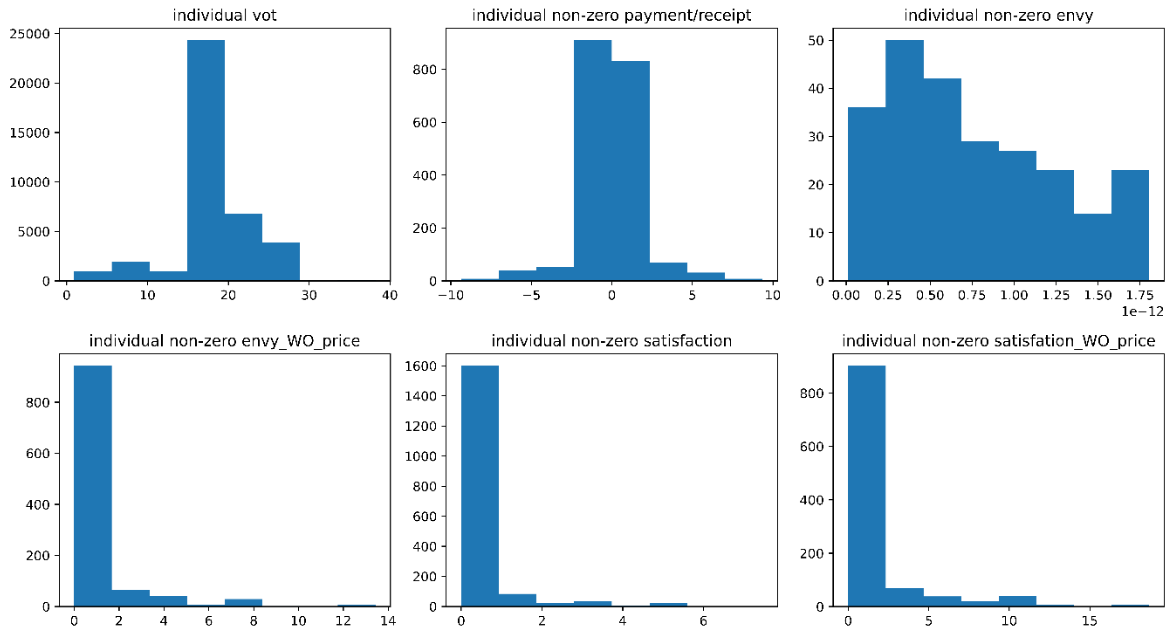
During this period, there are 38,818 agents entering the network. Among those agents, 1,951 agents (5%) participate in the price match. Among the 1951 agents with price matching, 941 agents pay, and 1010 agents receive the money. The total transaction among these 1,951 agents is $1,271.44, and the average transaction is $0.65. Their value of time, price paid or received, envy, extra benefit (shown as satisfaction, the negative of envy in the figures), envy without pricing, extra benefit (satisfaction) without pricing is shown in Figure 9. Most agents have zero individual payment/receipt, individual envy, individual satisfaction, individual envy_without_price and individual satisfaction_without_price.

Figure 9. Individual equity metrics among selected 38,818 agents



To better understand the distribution of these equity metrics among agents, we exclude all the zero values of payment/receipt, envy, envy without price, extra benefits (satisfaction or negative of envy), and satisfaction without price. The distributions are visualized in Figure 10. Most payments range from $-7 to $7. Non-zero envy after price matching is in the magnitude of 1e-12, which could be regarded as zero, while most of the envy without price matching are less than $4. Most extra benefit (i.e. level of satisfaction) after price matching are less than $2, while most of the satisfaction without price matching are less than $10.

Figure 10. Individual non-zero equity metrics among selected 38,818 agents



To understand who benefit from this platform, we plot the equity metrics for all the participants i.e., those who pay or receive in Figure 11, and the payers and receivers VOTs are visualized in Figure 12, not just agents with high VOT of 15-24 make a payment, but agents whose VOTs range from 0 to 10 also make a payment. Not just agents with low VOT, ranging from 0-10, receive money, but agents with high VOTs also receive money.

Figure 11. Individual equity metrics among 1,951 participants

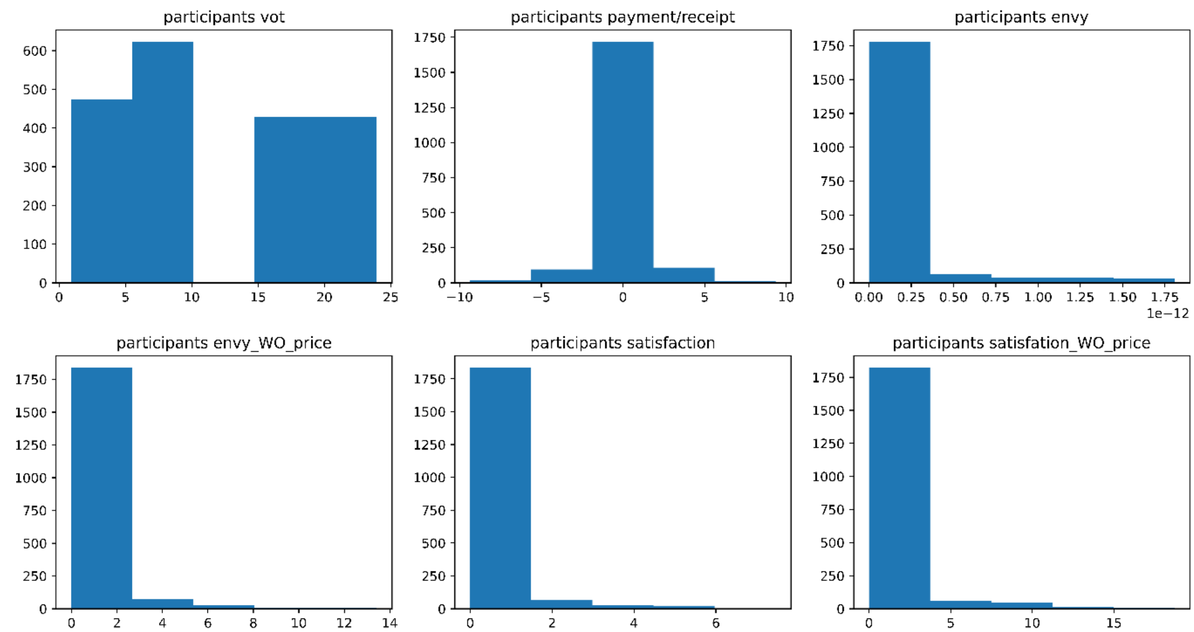
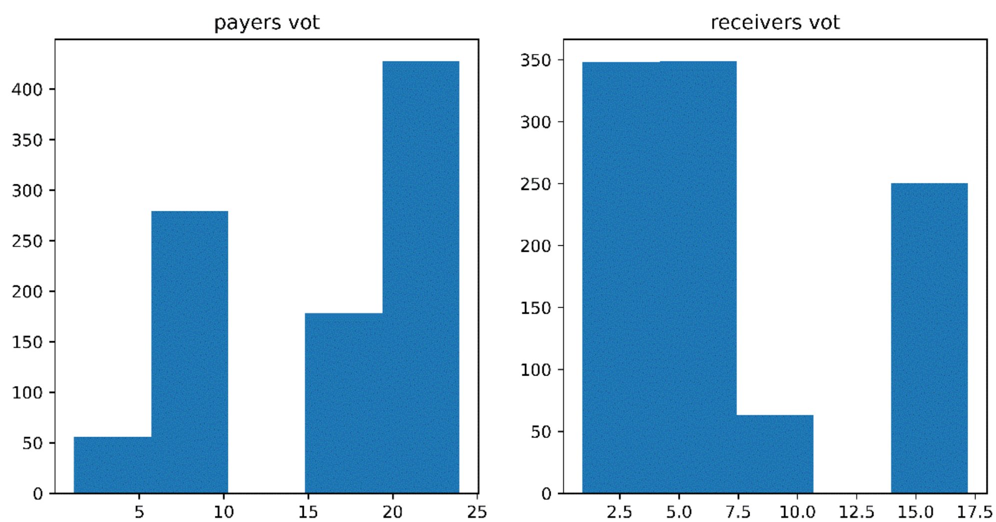


Figure 12. VOT distribution of 941 payers and 1,010 receivers



As Figure 12 shows, this platform could be used by different VOT groups, namely different income groups, to eliminate their envy via price matching.

Agent level equity metrics analysis among different income groups

Among these 1,951 participants, VOT ranges from 0.931 $/hr to 23.94 $/hr. When converting the VOT to the annual household income, the household income ranges from $6331 to $162,792. From 2013 American Community Survey[4], in the year of 2013, Households in Los Angeles county have a median annual income of $54,529 and mean income of $80,682.

We divided the income into three categories: the low-income group ($6,331-$50,000), middle-income group ($50,001-$120,000), and high-income group ($120,001-$162,792). Accordingly, the VOT in the low-income group, middle income group, and high-income group are (0.931-7.35), (7.36-17.64), and (17.65-23.94). Among the 1,951 participants, 902 of them are in the low-income group, 621 of them are in the middle income-group, and 428 of them are in the high-income group.

Figure 13. Distributions of equity metrics across low-, middle- and high-income group

[4]https://data.census.gov/cedsci/map?q=mean%20income%202013&g=0400000US06%248600000&tid=ACSST5Y2013.S1902&cid=S1902_C01_001E&vintage=2013&layer=VT_2013_860_00_PY_D1&mode=thematic&loc=34.0664,-118.0413,z11.1966

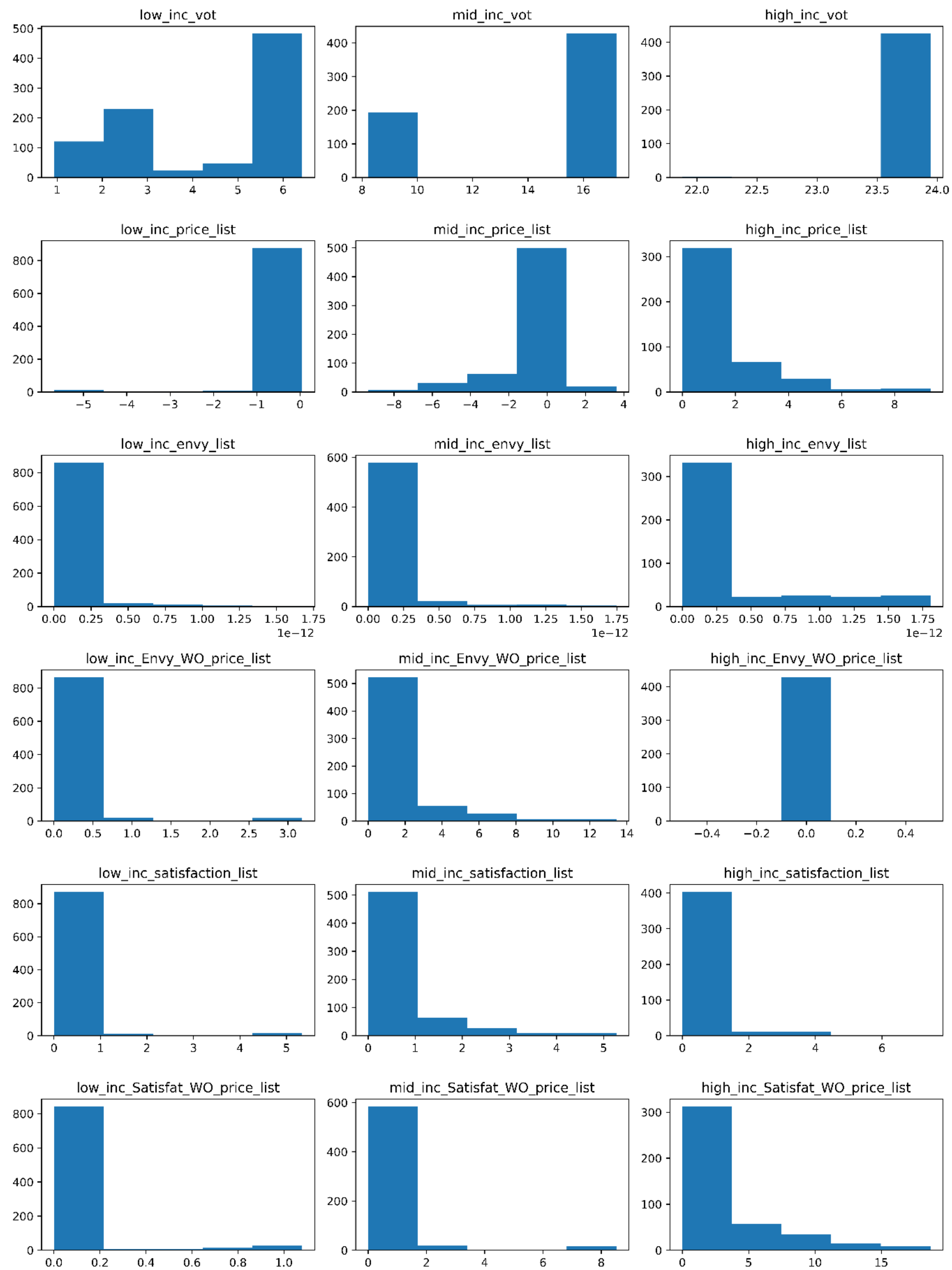

low_inc_vot
mid_inc_vot
high_inc_vot
low_inc_price_list
mid_inc_price_list
high_inc_price_list
low_inc_envy_list
mid_inc_envy_list
high_inc_envy_list
1e−12
low_inc_Envy_WO_price_list
mid_inc_Envy_WO_price_list
high_inc_Envy_WO_price_list
low_inc_satisfaction_list
mid_inc_satisfaction_list
high_inc_satisfaction_list
low_inc_Satisfat_WO_price_list
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Figure 13 shows the distributions of equity metrics across low-, middle- and high-income groups. The three histograms in the first row represent the VOT distributions of low-, middle- and high-income groups, which aligns with the definition of these three groups classified by their VOT. The three histograms in the second row represent the price the participants pay or receive. From these three histograms, low-income participants always receive incentives, and high-income participants always pay. Participants in the middle-income group would either pay or receive.

For the third row of histograms in Figure 13, the envy after pricing across all income groups decreases to 1e-12, which is close to zero, and all income groups reach the envy-free condition.

For the fourth row of histograms, the envy without pricing for high income groups is at zero, while most of the envy without pricing for the low-income groups are less than $1.0. The middle income group participants have more envy than low income group participants before the price matching.

The fifth and sixth rows of the histograms represent the level of satisfaction (extra benefits) before and after pricing for different income groups. High income group participants have the highest satisfaction. After price matching, their satisfaction distribution shifts to the left, which means that their level of satisfaction decreases. The satisfaction distributions of participants in the middle-income group shift more to the right after pricing, which means their level of satisfaction increases. Satisfaction of low-income groups increases after price matching.

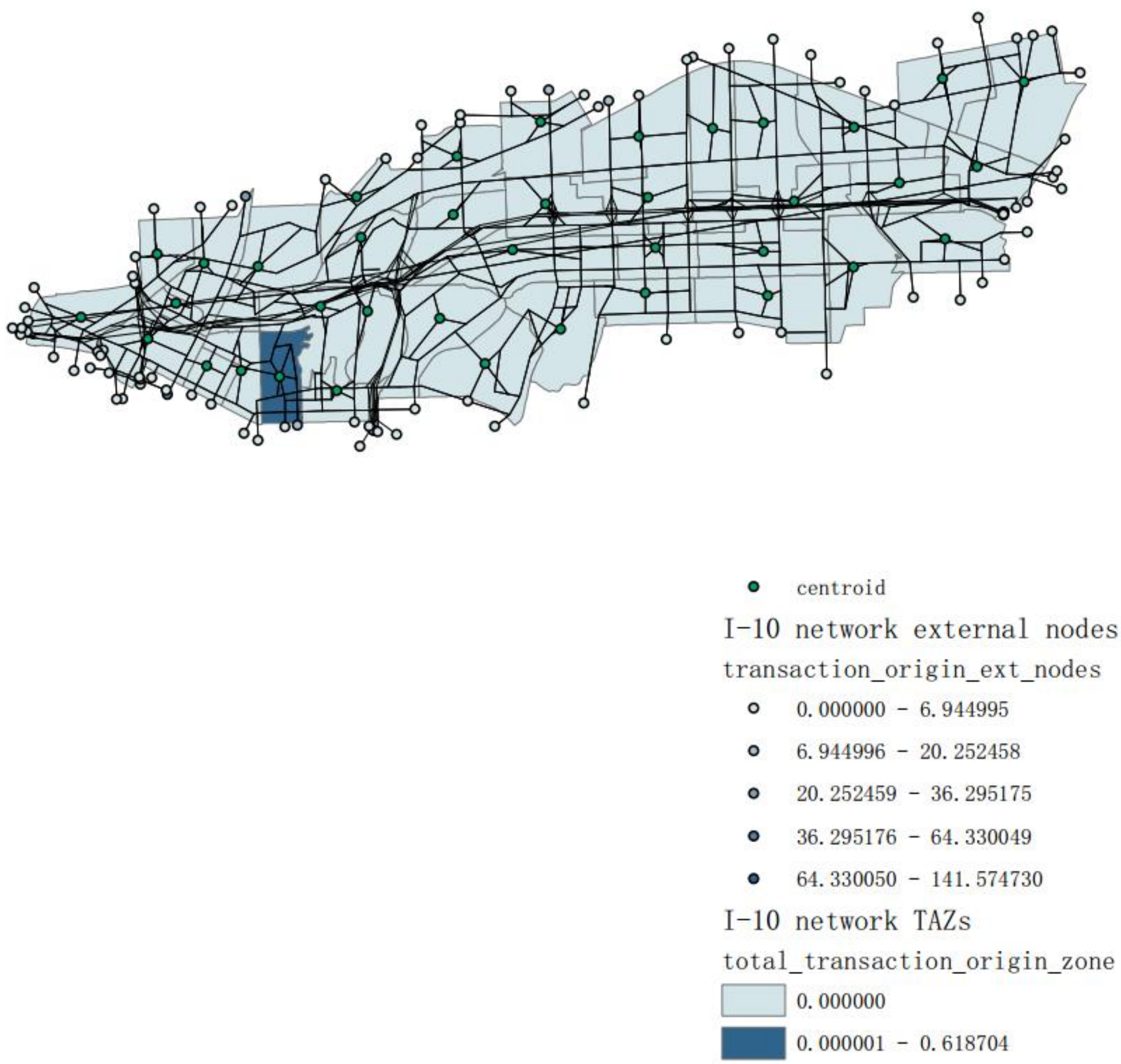
In summary, middle- and high-income groups all benefit from the proposed platform. Based on the allocation efficiency condition, agents from high income groups don't feel envy, and they pay others to use the shortest route. Due to the payments they made, satisfaction for high-income people decreases. For the low-income people, their envy is reduced to zero due to the price they receive. For the middle-income group people, they either make payments or receive incentives, and their envy is also reduced to zero while their satisfaction increases after price matching.

Zonal-level equity metrics analysis

In this section, we further analyze the zonal-level equity metrics. To understand what kind of agents benefit from this platform, we plot the zonal distribution of total transactions for all agents with their origin zones in Figure 14. As described in the "Supply data: the East Los Angeles I-10 Network" section, the network has 38 TAZs centroids and 60 external nodes. Among these 98 nodes, agents from only 18 of them have non-zero transactions (i.e. transaction happens for agents from these nodes.).

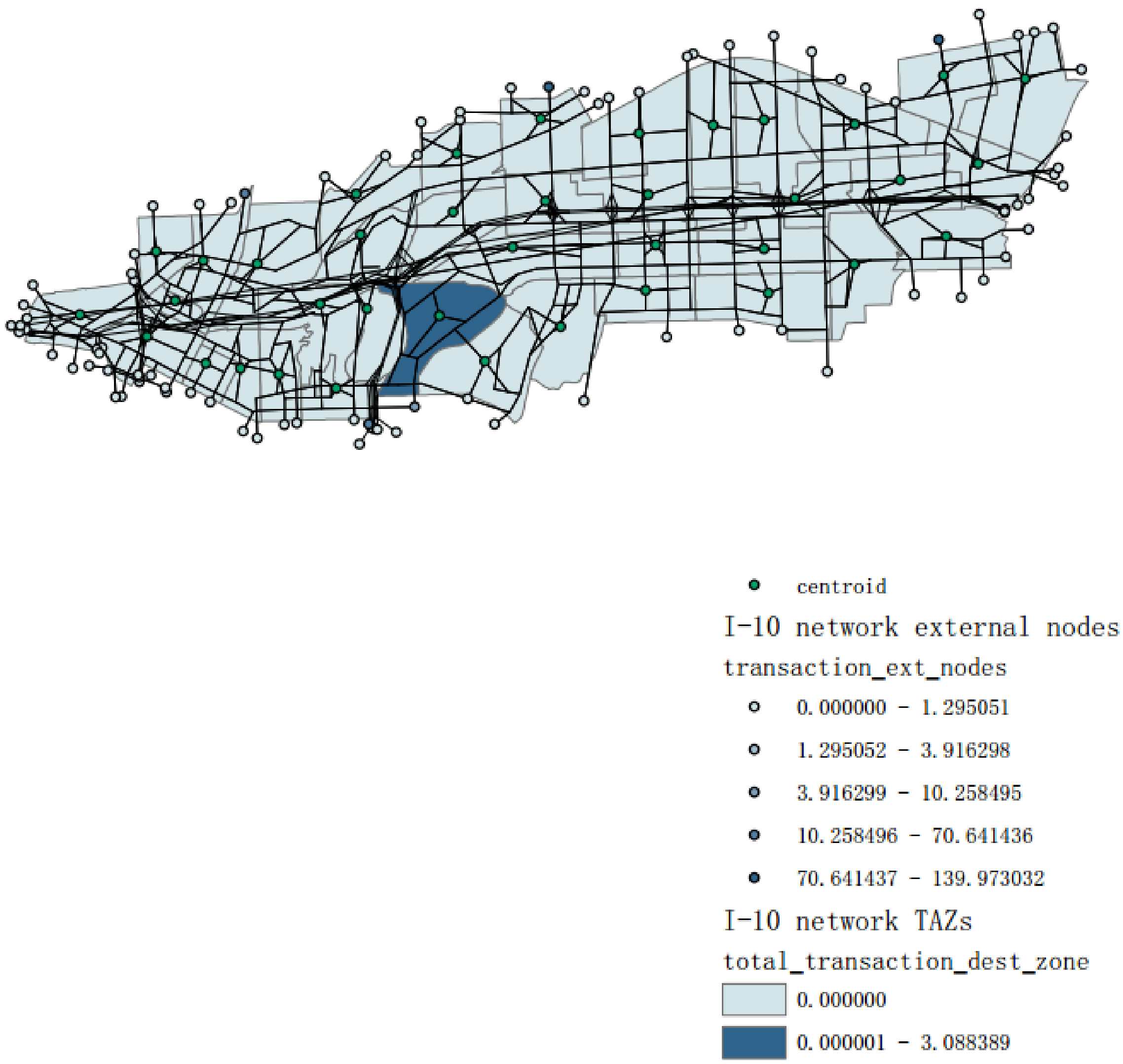
Among 18 nodes with non-zero transactions, 17 of them are external nodes. Only one is a TAZ centroid. Geographically, these 18 zones include external nodes along I-10 freeway both eastbound and westbound, external nodes along I-710 from south to north, and external nodes along I-5 both northbound and southbound. As mentioned in "Supply data: the East Los Angeles I-10 Network" section, there are three major highways passing through the I-10 network, which are - I-10 freeway, I-5 freeway, and I-710 freeway. These freeways will bring a great amount of through traffic into this I-10 network. As the traffic becomes more congested, multiple paths are found, and agents feel envy due to the differences in path travel time. Therefore, the transactions happen through traffic trips.

Figure 14. Zonal distribution of total transaction (origin zones)



Besides, we also plot the zonal distribution of total transactions for all agents with their destination zones in Figure 15. Among 20 destination zones where a transaction happens (transaction not equal to zero), 19 of them are external nodes. Only one is TAZ. Similar to trips' origin zones, trip destination zones are also in the external nodes of main freeways including I-10, I-5, I-710 and state route 19/State Route 164.

Figure 15. Zonal distribution of total transaction (destination zones)



From Figure 14, we know that most transactions occur with agents whose origin are external nodes. From Figure 15, we know that most transactions occur with agents whose destination are external nodes. In summary, for those agents participating in the transactions, most of them are through traffic agents. They will benefit from the price matching enabled by the proposed platform.

Conclusion

In this report, we introduced a smart mobility platform with fair congestion pricing and efficiently distributed incentives to agents who are willing to yield their shortest paths. The model contributes to the redistribution of the travel budget to low-income people as a travel credit.

The platform has two components, a dynamic traffic assignment simulator component and an envy-minimization price matching component. The simulator illustrates reasonable dynamic traffic assignment traffic results, and the DSO could be achieved. Compared with the DUE, which is regarded as the real-world condition, DSO makes the VMT in our model increase by 7%, while the VHT decreases by 5%, resulting in a 13% increase of agent space mean speed from 31.24 mph to 35.32 mph. The model makes the traffic less congested.

Not only can this platform make the system more efficient, but it could also make the system fairer through the envy-minimization price matching mechanism. After price matching, although high income agents' levels of satisfaction (i.e., extra benefits) decrease, the envy for all participant agents is reduced to zero, making the network envy-free.

To further understand the characteristics of the participant agents, we further divided the participants into three different income groups according to their value of time - low-income group, middle-income group, and high-income group. We found that agents from high-income groups make payments, and the ones from low-income groups receive money, while those from middle-income groups either pay or receive. As for envy before price matching, agents from the middle-income group have even larger envy than the low-income group, while agents from the high-income group have zero envy. After price matching, agents' envy for all income groups could be reduced to zero. The satisfaction (i.e., negative of envy) for agents from high-income groups decreases, while satisfaction for those from low- and middle-income groups increases after the price match.

To further understand spatial characteristics of the participants, we analyzed the total zonal transaction in terms of the agents' origins and destinations. We found that most price matching happen on through trips in which agents travel on major freeways through the network, like I-10, I-5 and I-705.

In this report, we found that the proposed fair and efficient transportation platform which could not only represent realistic traffic conditions, but also make the system fairer and more efficient. The platform could be used to analyze the spatial equity issues within the network. As the tolls could fund public transportation systems, it could motivate travelers to shift to transit systems. We are interested in further introducing public transit systems and analyzing the multi-model impact on the transportation system. Additionally, we are also interested in further analyzing the impact that the proposed mobility systems have on personal vehicle ownership.

References

1. Zhou L, Burris MW, Baker RT, Geiselbrecht T. Impact of incentives on toll road use by trucks. Transp Res Rec. 2009;(2115):84–93.

2. Arnott R, Palma A De, Lindsey R. The Welfare Effects of Congestion Tolls with Heterogeneous Commuters. J Transp Econ Policy [Internet]. 1994;28(2):139–61. Available from: http://www.jstor.org/stable/20053032%5Cnhttp://www.jstor.org/stable/pdfplus/20053032.pdf

3. Nie YM. Transaction costs and tradable mobility credits. Transp Res Part B Methodol [Internet]. 2012;46(1):189–203. Available from: http://dx.doi.org/10.1016/j.trb.2011.10.002

4. Ben-Elia E, Tillema T, Ettema D. Road pricing vs. peak-avoidance rewards: A comparison of two Dutch studies. 12th World Conf Transp Res [Internet]. 2010; Available from: http://www.civil.ist.utl.pt/wctr12_lisboa/proceedings.htm

5. Nam D. Modelling and Optimization of Smart Mobility Systems with Agent Envy as a Paradigm for Fairness and Behavior [Internet]. UC Irvine; 2019. Available from: https://escholarship.org/uc/item/3ns0h561

6. Bento A, Kevin R, Waxman A. Avoiding traffic congestion externalities? the value of urgency [Internet]. National Bureau of Economic Research. 2020. Available from: https://www.nber.org/papers/w26956

7. Merchant DK, Nemhauser GL. A Model and an Algorithm for the Dynamic Traffic Assignment Problems [Internet]. Vol. 12, Source: Transportation Science. 1978. Available from: https://about.jstor.org/terms

8. Peeta S, Ziliaskopoulos AK. Foundations of dynamic traffic assignment: The past, the present and the future. Networks Spat Econ. 2001;1(3):233-265.

9. Friesz TL, Luque J, Tobin RL, Wie B-W. Dynamic Network Traffic Assignment Considered as a Continuous Time Optimal Control Problem. Vol. 37, Source: Operations Research.

10. Mahmassani H, Peeta S. Network performance under system optimal and user equilibrium dynamic assignments: implications for advanced traveler information systems. In: Transportation Research Record 1408. 1993. p. 83.

11. Jayakrishnan R, Mahmassani HS, Hu T-Y. An evaluation tool for advanced traffic information and management systems in urban networks. Transp Res Part C Emerg Technol. 1994;2(3):129–47.

12. Mahmassani HS, Fei X, Eisenman S, Zhou X, Qin X. DYNASMART-X evaluation for real-time TMC

application: CHART test bed. 2005.

13. Zhou X, Taylor J. DTAlite: A queue-based mesoscopic traffic simulator for fast model evaluation and calibration. Cogent Eng. 2014;1(1).

14. Jayakrishnan R, Tsai WK, Chen A. A dynamic traffic assignment model with traffic-flow relationships. Transp Res Part C Emerg Technol. 1995;3(1):51–72.

15. Yang I, Jayakrishnan R. Gradient projection method for simulation-based dynamic traffic assignment. Transp Res Rec. 2012 Jan 12;(2284):70–80.

16. Jayakrishnan R, Tsai WT, Prashker JN. A Faster Path-Based Algorithm for Traffic Assignment. In: Transportation Research Record 1443 [Internet]. 1994. p. 75–83. Available from: https://escholarship.org/uc/item/2hf4541x

17. Gentile G. Solving a Dynamic User Equilibrium model based on splitting rates with Gradient Projection algorithms. Transp Res Part B Methodol [Internet]. 2016;92:120–47. Available from: http://dx.doi.org/10.1016/j.trb.2016.02.005

18. Small KA. Using the revenues from congestion pricing. Transportation (Amst). 1992;19(4):359–81.

19. Dial RB. Network-optimized road pricing: Part II: algorithms and examples. Oper Res. 1999;47(2):327–36.

20. Liu LN, McDonald JF. Efficient Congestion Tolls in the Presence of Unpriced Congestion: A Peak and Off-Peak Simulation Model. J Urban Econ. 1998;44(3):352–66.

21. Yang H, Wang X. Managing network mobility with tradable credits. Transp Res Part B Methodol [Internet]. 2011;45(3):580–94. Available from: http://dx.doi.org/10.1016/j.trb.2010.10.002

22. Nie Y (Marco). A New Tradable Credit Scheme for the Morning Commute Problem. Networks Spat Econ. 2015;15(3):719–41.

23. Nie YM, Yin Y. Managing rush hour travel choices with tradable credit scheme. Transp Res Part B Methodol [Internet]. 2013;50:1–19. Available from: http://dx.doi.org/10.1016/j.trb.2013.01.004

24. He F, Yin Y, Shirmohammadi N, Nie YM. Tradable credit schemes on networks with mixed equilibrium behaviors. Transp Res Part B Methodol [Internet]. 2013;57:47–65. Available from: http://dx.doi.org/10.1016/j.trb.2013.08.016

25. Pan J, Khan MA, Popa IS, Zeitouni K, Borcea C. Proactive vehicle re-routing strategies for congestion avoidance. Proc - IEEE Int Conf Distrib Comput Sens Syst DCOSS 2012. 2012;(1):265–72.

26. Liu R, Liu H, Kwak D, Xiang Y, Borcea C, Nath B, et al. Themis: A participatory navigation system for balanced traffic routing. IEEE Veh Netw Conf VNC. 2015;2015-Janua(January):159–66.

27. Djavadian S, Hoogendoorn RG, Van Arem B, Chow JYJ. Empirical evaluation of drivers' route choice behavioral responses to social navigation. Transp Res Rec. 2014;2423:52–60.

28. Verhoef E, Nijkamp P, Rietveld P. Second-best regulation of road transport externalities. J Transp Econ Policy. 1995;29(2):147–67.

29. Roughgarden T. How unfair is optimal routing? Proc Annu ACM-SIAM Symp Discret Algorithms.

2002;06-08-Janu:203–4.

30. Ben-Elia E, Ettema D. Carrots versus sticks: Rewarding commuters for avoiding the rush-hour— a study of willingness to participate. Transp Policy J. 2009;16(2):68–76.

31. Boyce D, Xiong Q. User-Optimal and System-Optimal Route Choices for a Large Road Network. Rev Netw Econ. 2009;3(4):371–80.

32. Barbanel JB, Taylor AD. The geometry of efficient fair division. Geom Effic Fair Div. 2005;29(Dec):1–462.

33. Gamov G, Stern M. Puzzle math. New York: Viking; 1958.

34. Varian HR. Equity, envy, and efficiency. J Econ Theory. 1974;9(1):63–91.

Data Management Pl

Products of Research

Describe the data that were collected and used for the study.

1. Data

a. Los Angeles County I-10 network data

b. Los Angeles County I-10 network trip table from California Statewide Travel Demand Model (CSTDM) demand data

c. Los Angeles County zonal VOT data from 2013 Los Angeles County average household income data [5]

2. Software/Algorithms

a. agent-based path-based dynamic traffic assignment simulation model

b. gradient projection algorithm

c. gurobi solver

Data Format and Content

Describe the format, or file type, of the data, and the contents of each file.

1. Los Angeles County I-10 network data:

a. links_L20.csv - Contains the Los Angeles County I—10 network link level data.

b. nodes.csv - Contains the Los Angeles County I—10 network node level data.

2. Los Angeles County I-10 network trip table:

a. trips_multiple(134).csv- Los Angeles County I-10 network trip table from California Statewide Travel Demand Model (CSTDM) demand data

3. Los Angeles County zonal VOT data:

a. zonal_vot_info.csv- Contains mean and standard deviation of zonal VOTs among the I-10 network.

Data Access and Sharing

The data and software are available at the following link:
https://datadryad.org/stash/share/Wz0uJ9u9eeq4S_thyKofuzcEgbQjIE0IuA3bOBj_t70

[5] https://data.census.gov/cedsci/map?q=mean%20income%202013&g=0400000US06%248600000&tid=ACSST5Y2013.S1902&cid=S1902_C01_001E&vintage=2013&layer=VT_2013_860_00_PY_D1&mode=thematic&loc=34.0664,-118.0413,z11.1966